


Measurement Practices in UX Research: A Systematic Quantitative Literature Review


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Abstract

User experience research relies heavily on survey scales to measure users' subjective experiences with technology. However, repeatedly raised concerns regarding the improper use of survey scales in UX research and adjacent fields call for a systematic review of current measurement practices. Therefore, we conducted a systematic literature review, screening 153 papers from four years of the ACM Conference on Human Factors in Computing Systems proceedings, of which 60 were eligible empirical studies using survey scales to study users' experiences. We identified 85 different scales and 172 distinct constructs measured. Most scales were used once (70.59%), and most constructs were measured only once (66.28%). Furthermore, results show that papers rarely contained complete rationales for scale selection (20.00%) and seldom provided all scale items used (30.00%). More than a third of all scales were adapted (34.19%), while only one-third of papers reported any scale quality investigation (36.67%). On the basis of our results, we highlight questionable measurement practices in UX research and suggest opportunities to improve scale use for UX-related constructs. Additionally, we provide recommendations to promote improved rigor in following best practices for scale-based UX research.

Keywords: Literature review; Questionnaires; Survey Scales; User Experience; UX; Measurement; Constructs; Questionable Measurement Practices; QMPs

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Introduction

Survey scales, sometimes called questionnaires or rating scales, are one of the most commonly used methods for measurement with a long history, originating in the social sciences (Gault, 1907). Human-Computer Interaction (HCI) research has adapted this method to measure the experiences people have when interacting with technology (Cairns & Power, 2018). Within user experience (UX) research specifically, survey scales account for one of the most popular methods to collect data (Bargas-Avila & Hornbæk, 2011; Pettersson et al., 2018). One of the more fundamental sources, DeVellis (2017), defines survey scales as *"collections of items combined into a composite score and intended to reveal levels of theoretical variables not readily observable by direct means"* (DeVellis, 2017, p. 15). We adopt this definition, as well as the terms used by DeVellis (2017) and refer to methodological approaches fitting this definition as *survey scales*. Essentially, survey scales use a set of items to measure a construct that is of interest to a researcher (DeVellis, 2017). We will use the term *construct* to refer to unobservable aspects relevant to UX research, such as psychological traits or abilities of individuals (Hopkins, 1998). For example, "trust in automation" is a construct defined by UX researchers on the basis of patterns of thoughts and behaviors indicating subjective trust. This construct can then be made accessible with a survey scale by having users respond to the 12 items of the "Trust between People and Automation" scale (Jian et al., 2000). The users' responses to the scale's items can then be combined, for example, by forming an overall score or calculating the mean value. This process provides the researcher with a number reflecting users' subjective levels of trust toward the automated system. The resulting number can then be used for statistical analysis during the research process and compared across experiments when the same scales are used more than once.

While survey scales are a powerful method, offering many benefits to researchers (Nunnally, 1978), researchers can only have confidence in the data gathered and the

conclusions derived from said data when appropriate scales are used with proper rigor (Furr, 2011). In turn, if survey scales used to measure a construct lack validity or are misused, the quality of the data collected is negatively affected, and a study's conclusions have to be put into question (Flake & Fried, 2020). Work from fields related to UX, such as social and personality psychology, has raised doubts regarding the quality of some of the most frequently used survey scales in these respective disciplines (Flake et al., 2017; Hussey & Hughes, 2020). On this matter, Flake and Fried (2020) recently introduced the term questionable measurement practices (QMPs), referring to *"decisions researchers make that raise doubts about the validity of measure use in a study, and ultimately the study's final conclusions"* (Flake & Fried, 2020, p. 2). Thus, if researchers use survey scales for data collection without sufficient rigor, they expose their study to potential QMPs. Examples of such QMPs include a lack of evidence for the quality of a scale (e.g., for the scale's validity) or unjustified flexibility in employing the scale (e.g., removing or changing items). Most of the time, QMPs do not occur with malicious intent but because scientists face difficult decisions during all stages of the research process, including when working with survey scales, but also when other methods are used (Flake & Fried, 2020). Furthermore, if there is little to no information on how a scale was employed in a study, it can be hard, if not impossible, to judge the validity of the scale and the study as a whole. Thus, the absence of transparency hinders the identification and the prevention of QMPs (Flake & Fried, 2020).

Recent findings from the field of player experience (PX) research have shown that there is a lack of transparent reporting in studies that employ survey scales for measurement, indicating the presence of QMPs in PX research (Aeschbach et al., 2021). Given the close relation between UX and PX research, it is plausible that comparable practices likewise exist in UX research. Considering past findings from UX research, early indications for the existence of QMPs are evident. Bargas-Avila and Hornbæk (2011) raised concerns regarding the way UX researchers use scales as a method, such as an over-reliance on self-developed items and nontransparent reporting regarding the scale items used (Bargas-Avila & Hornbæk, 2011). More recently, Pettersson et al.

(2018) found that self-developed scales are still more popular in UX research compared to scales taken from previous research. Based on Flake and Fried (2020), we see a potential risk for QMPs in UX research whenever researchers do not follow best practices or rather do not report on following them. However, there is no systematic analysis of QMPs' prevalence in UX research. We, therefore, set out to identify current best practices based on literature from past HCI research, psychometrics, and the social sciences (Aeschbach et al., 2021; DeVellis, 2017; Furr, 2011; Nunnally, 1978), and systematically investigated how well scale-based UX research follows these best practices.

If UX research is at risk of QMPs, and a lack of following best practices can be observed when employing scales, addressing these issues would come with great potential for UX research. Due to the subjective nature of UX and the potential of survey scales as a method for data collection, we see a great prospect in the proper use of survey scales as a method to quantify people's subjective experience through indirect means (DeVellis, 2017). However, systematic knowledge of current practices in scale-based research is needed to understand where UX research currently needs more adherence to best practices, hindering it from reaping the full potential of survey scales. By comparing how survey scales have been employed in UX research with current "best practice" from the literature on survey scales and psychometrics (DeVellis, 2017; Furr, 2011; Nunnally, 1978), we aim to see where UX research stands and if there is room for improvement in scale-based UX research. From this, we can provide clear recommendations addressing the identified issues, helping future research use survey scales with even more potential, fostering methodologically improved UX research and a better understanding of UX.

Background

In the field of HCI, whether survey scales are an appropriate method to study UX has frequently been questioned (Law et al., 2014). In particular, past research has uncovered skepticism among UX researchers towards the reductionist process of

breaking down a user's experience into constructs to make it measurable, arguing that it goes against the holistic notion of UX, oversimplifying the complexity of a user's experience (Law et al., 2014). In defense of survey scales, Cairns and Power (2018) argued that proper use of modern psychometric methods could acknowledge this contradiction between a holistic view of experiences and the reductionist measurement process. By using modern statistical methods, researchers can form richer interpretations of the data gathered using survey scales, therefore offering a more differentiated picture of UX (Cairns & Power, 2018). Yet, research findings by Law et al. (2014) contain an argument that the challenge with measuring UX is not measurement itself, but rather that UX researchers need enhanced training and education on how to measure. Measurement of UX becomes problematic when researchers do not understand the measures they are utilizing, are unaware of certain limitations that come with them, over-formalize them or intentionally misuse them (Law et al., 2014). Thus, it appears that the problem with measurement using survey scales in UX research is not the method itself but problems that arise when researchers use these scales without following current best practices.

Best practices in measurement using scales

The following section provides an accessible overview of some essential ideas and best practices behind measurement using scales that we considered in our review to investigate how UX researchers use survey scales. While some of these ideas are derived from suggestions on avoiding QMPs (Flake & Fried, 2020), others are based on additional literature on survey scales and measurement within the social sciences (DeVellis, 2017; Furr, 2011; Nunnally, 1978).

Standardized or self-developed scales

Survey scales, ideally, are developed as part of a process specifically aimed at creating a new scale to measure one or more constructs. Items are carefully formulated based on theoretical concepts to cover all relevant aspects of a construct, and the quality of the scale (e.g., its reliability and validity) is examined using appropriate

statistical methods (DeVellis, 2017). Based on the results from the quality investigation, the scale and its items are then revised and re-investigated in an iterative development process until a final version of the scale is established (Furr, 2011). Researchers can then use the final scale across studies and, ideally, without modification (Juniper, 2009). In some cases, however, scales are assembled, and their items are written without much theoretical thought guiding the process (DeVellis, 2017). Such scales are typically created as part of a specific study and are rarely used across multiple ones. Therefore, researchers arguably invest less thought and effort into the precise wording of the items, and little to no effort is made to examine the quality of the scale. The former type of carefully developed scales is typically referred to as "validated" or "standardized" scales, while frequently used terms for the latter type are "self-developed" or "ad hoc" scales.

A standardized scale offers researchers many advantages, such as objectivity, reliability, and the possibility of scientific generalization (Nunnally, 1978). Researchers may lose some, if not all, of these advantages when using self-developed scales. The list of studies advocating for standardized scales in HCI research is long (e.g., Hornbæk, 2006; Hornbæk & Law, 2007; Sauro & Lewis, 2009). Nevertheless, several articles have demonstrated an over-reliance on self-developed scales in usability (Hornbæk, 2006; Hornbæk & Law, 2007) and UX research (Bargas-Avila & Hornbæk, 2011; Pettersson et al., 2018). Thus, we see a need to investigate the type of scales authors use (self-developed or standardized) to determine if UX research still shows an over-reliance on self-developed scales.

Transparent reporting of scale items

When using scales, researchers should share the exact wording of the items they used in their research (Flake & Fried, 2020). Sharing the items used allows readers to judge which version of a scale was employed, if or how items were adapted, and how adequate the items were for the research effort in general. Given factors such as differing scale versions (e.g., short vs. long, varying languages), adaptations of items, and sometimes unclear citations for those scale versions, it can sometimes be unclear which version of a scale was used, even if the scale is a standardized scale. Transparency

regarding the items used is vital because differences in how a scale was employed can influence a study's results, introducing methodological variability across the research literature (Flake & Fried, 2020). In addition to helping other researchers better understand a study (Flake & Fried, 2020), transparency regarding study materials, such as scale items, makes replications possible (Wacharamanotham et al., 2020). However, past research has shown that reporting items is uncommon in scale-based UX research (Bargas-Avila & Hornbæk, 2011). Given these previously negative findings and the importance of sharing items (Flake et al., 2017), we find a need for an updated investigation into the transparency of the reporting of scale items.

Providing a rationale for scale selection

Because there are numerous scales available to measure a particular target construct, it can be difficult for researchers to select an appropriate scale for their research purpose. While there are always arguments for or against using a particular scale, Flake and Fried (2020) argued that researchers need to provide a clear rationale for why they chose a specific scale based on theoretical as well as empirical and practical reasoning. According to Aeschbach et al. (2021), a good rationale contains the definition of the target construct, the theory behind the construct, and how the target construct was operationalized (i.e., how it was measured). Furthermore, details on the administration process of a scale (e.g., number of items) and evidence for a scale's validity (i.e., content, criterion, and construct validity) need to be reported (Aeschbach et al., 2021). Providing complete rationales helps readers and reviewers judge the adequacy of said scale for measuring the target construct. In addition, forming such rationales forces the researchers to critically consider the appropriateness of the scale they used (Flake & Fried, 2020). Recent findings from PX research have demonstrated that rationales for scale selection are rare (Aeschbach et al., 2021). Regarding UX research, no comparable investigation exists. We thus see a need to investigate how often UX researchers offer any form of rationale when using survey scales.

Adapting scales

As mentioned above, standardized scales usually undergo an elaborate development process to ensure their quality. Therefore, scales used in research should ideally not be adapted because even the slightest adaption could change the scale's psychometric quality (Furr, 2011; Juniper, 2009). Because adapting a scale can alter the scale's quality compared to the original validated version, adapted scales should be considered closer to self-developed scales rather than previously validated scales (Furr, 2011). In addition, adapting existing scales jeopardizes measurements' comparability across the published literature (Flake & Fried, 2020). Recent findings by Aeschbach et al. (2021) have shown that PX researchers frequently adapt their measures when using them. Therefore, we identify a need to investigate the rate of scale adaption in current UX research.

Determining the quality of scales

Researchers must ensure that the quality of the scales they use for measurement is adequate because their collected data, and thus their conclusions, depend on their method. Whenever a scale is used, its quality needs to be investigated to ensure it performs as expected within that specific study (Furr, 2011). Regarding scale quality, there are typically three main criteria to consider: objectivity, reliability, and validity (DeVellis, 2017).

Objectivity is concerned with the notion that *"any statement of fact made by one scientist should be independently verifiable by other scientists"* (Nunnally, 1978, p. 6). Carefully developed measurement methods, such as validated or standardized scales, typically bring with them the advantage of leaving little room for disagreement (Nunnally, 1978). Given this advantage, objectivity is one of the key arguments behind standardized scales.

Reliability is defined as *"how accurately a test measures the thing which it does measure"* (Kelley, 1927, p. 14). When trying to find indicators of a scale's reliability, Dunn et al. (2014) recommended that researchers ideally report both coefficients alpha

(Cronbach, 1951) and omega (McDonald, 1999). Regarding usability research, past work found that only a few studies report on any efforts of validation or reliability assessment (Hornbæk, 2006). Accordingly, we see a need to investigate if UX researchers report on coefficients alpha and omega when using scales for measurement.

Validity considers *"whether a test really measures what it purports to measure"* (Kelley, 1927, p. 14). One important class of statistical methods used to assess an essential aspect of validity (i.e., construct validity) is factor analysis (Cairns & Power, 2018). Here, we chose to focus on factor analysis, leaving out other forms of validity assessments, but refer readers to DeVellis (2017, Chapter 4) for a more extensive overview. The most common forms of factor analysis are exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA is used to identify the underlying scale structure, determining which factors (i.e., which constructs) are measured employing the scales' items. CFA, on the other hand, as its name indicates, is applied to confirm the underlying theoretical structure of a scale (Brown, 2015). Given that there is no systematic investigation into how often UX researchers calculate EFAs and CFAs when using survey scales, examining if UX researchers report these validity indicators when using survey scales seems warranted.

Questionable measurement practices

When it comes to measurement, researchers face difficult decisions, and with them, the risk of QMPs arises (Flake & Fried, 2020). QMPs contain actions such as changing the items of a standardized scale without providing clear reasoning or not defining constructs measured in the study. However, no definitive list of QMPs exists to date. They cover a whole range of issues, from a researcher's ignorance or negligence to intentionally misleading practices (Flake & Fried, 2020). At their core, QMPs are closely linked to nontransparent reporting because lack of transparency, intentional or unintentional, obscures actions regarded as questionable in research (Flake & Fried, 2020). The lack of transparent reporting makes it impossible to identify threats to the validity of the measurement scales used as well as the conclusions of a study using

scales (Flake & Fried, 2020). Therefore, while QMPs cover a range of different issues, it is hard to identify how frequent they are and what QMPs exist within a particular field of research if authors provide limited information on their measurement process (Flake & Fried, 2020).

While past research has highlighted specific problems within scale-based UX research, such as an over-reliance on self-reported scales (Bargas-Avila & Hornbæk, 2011; Pettersson et al., 2018) and a lack of transparent reporting (Aeschbach et al., 2021; Bargas-Avila & Hornbæk, 2011), the central role of survey scales in UX research and the emerging discussions about the correct application of this method (Aeschbach et al., 2021; Flake & Fried, 2020) call for a systematic review of the current use of survey scales in UX research.

Research objectives

To better understand how survey scales are used as a method in UX research, we investigated how frequently publications contain reports on the above-described best practices, indicating to what extent UX research might be affected by QMPs. In addition, we examined which specific survey scales are used and which constructs are measured with these survey scales to enhance understanding of current practices of scale use in UX research. Based on these research objectives, we formulated the following research questions:

RQ1: Which standardized scales are currently used in UX research?

RQ2: How frequently are standardized scales used in comparison to self-developed scales?

RQ3: How often are standardized scales adapted?

RQ4: What constructs do researchers measure using survey scales?

RQ5: How often do authors provide a rationale for using a specific scale?

RQ6: How often do authors provide the items of the scales used?

RQ7: How often do authors investigate the psychometric quality of the scales they use? And with what methods?

RQ8: How often are additional types of data (i.e., qualitative, behavioral) collected alongside self-reported quantitative data from scales?

Method: systematic quantitative literature review

We followed the systematic quantitative literature review (SQLR) process (Pickering & Byrne, 2014; Pickering et al., 2015). In addition, we adhered to the PRISMA 2020 statement (Page et al., 2021) in reporting this review, where applicable. Following the PRISMA-P statement (Moher et al., 2015), we pre-registered an initial protocol for this systematic review with OSF on October 16, 2020 (<https://doi.org/10.17605/OSF.IO/29ZYA>). Since then, our research strategy and focus have seen several amendments due to the nature of the SQLR. We describe these amendments in the latest version of the protocol on OSF.

Search strategy

Likewise to other reviews in HCI (e.g., Caine, 2016; Liu et al., 2014; Salehzadeh Niksirat et al., 2023; Tyack & Mekler, 2020), we focused on proceedings of the ACM Conference on Human Factors in Computing Systems (CHI). Consequently, we searched the ACM Digital Library (ACM DL, <https://dl.acm.org/>), specifically the ACM Guide to Computing Literature, considering all articles published as proceedings to CHI from 2019 to 2022. We decided to focus on CHI due to its reputation as one of the most prestigious venues for publishing HCI and UX-related research, as reflected in its high impact factor among HCI publications (h5-index of 113, h5-median of 154 (Google Scholar, 2022, March 17, 2023)). In addition, papers published at CHI are often considered representative of all research in HCI (Hornbæk, 2006). For our final search, we used the following search query:

[Abstract: "user experience"] OR [Abstract: ux] OR [Keywords: "user experience"] OR [Keywords: ux] OR [Title: "user experience"] OR [Title: ux] AND [E-Publication Date: (01/01/2019 TO 12/31/2022)]

We thus searched for the keywords "UX" or "user experience" in the titles, abstracts, and keywords. We further used the ACM DL's "Content Type" filter to include only records classified as "Research Article." In addition, we used the ACM DL's "Proceedings/Book Names" filter only to include results for the relevant CHI proceedings, one year at a time.

Criteria for inclusion and exclusion

We included all full paper articles reporting empirical studies of UX using scales for quantitative data collection, which gave us the following three inclusion criteria:

First inclusion criterion: full paper. We focused only on full papers classified as "Research Article" in the ACM DL, thus excluding entries marked as "Extended Abstract," "Poster," "Abstract," "Review Article," "Demonstration," "Short Paper," "Technical Note," "Tutorial," or "Panel." This inclusion criterion was mainly checked for using the ACM DL's "Content Type" filter during the initial search (filtering for "Research Article") and again assessed during the coding of the final sample.

Second inclusion criterion: empirical study. Due to our focus, we defined "empirical studies of UX" as research projects fitting the following criteria: (a) collect qualitative or quantitative data (b) from users' interactions (c) with a product (d) in an attempt to develop a better understanding of UX. We thus excluded publications that did not contain empirical studies gathering and reporting data from users (e.g., literature reviews, theoretical reflections) or did not consider users' interactions with a product to study UX (e.g., technical investigations of a new artifact without users). This inclusion criterion is comparable to the first criterion used by Bargas-Avila and Hornbæk (2011), where eligible studies were required to report on qualitative or quantitative data collected from users.

Third inclusion criterion: using scales. To define the term *scale* in line with our research objective, we used the definition for survey scales by DeVellis (2017). We also decided to include papers using single-item scales from previous literature, such as the Net Promoter Score (NPS, Reichheld, 2003) and the Subjective Mental Effort

Question (SMEQ, Zijlstra & Van Doorn, 1985). Thus, we also included all articles reporting on using single-item scales if authors gave a citation for those single items.

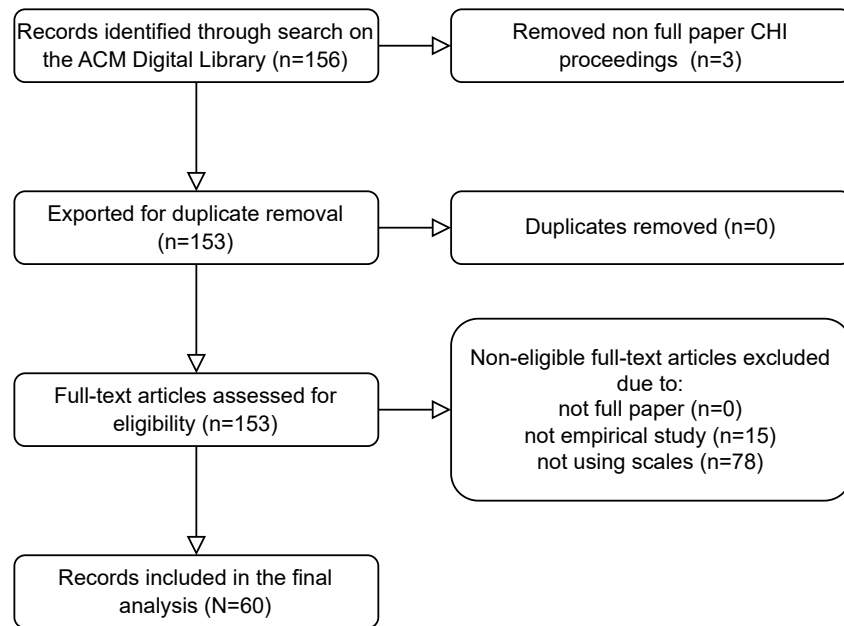
Papers only using self-created single items (without a citation) were not eligible, considering they did not fit the chosen definition of a scale. Studies only using non-UX scales (scales used to measure constructs unrelated to UX research) were also non-eligible due to our focus on UX research. However, we did include scales unrelated to UX research if they were used alongside UX-related scales to study topics of UX research. Studies only using scales in preliminary studies (e.g., pilot studies) without any details (e.g., just mentioning that a scale was used without reporting results) were also excluded because coding them with confidence would have been hard, if not impossible.

Definitive search and initial sample

We conducted our definitive search in the ACM DL on March 22, 2023, yielding 156 search results for our search query. After the initial search, we excluded three records because they were not full papers published as proceedings to CHI (e.g., extended abstracts). Citation info and abstracts for the remaining 153 records were then exported to check for duplicate entries. No duplicate records were identified. Thus, all 153 entries were uploaded into a shared spreadsheet for the creation of our codebook and the coding of eligibility. The final sample screened for eligibility consisted of 37, 43, 30, and 43 unique records for 2019, 2020, 2021, and 2022, respectively. Figure 1 summarizes our complete study selection process as a PRISMA flow diagram. The complete list of all 153 records considered for eligibility can be found in the codebook on OSF.

Data collection process

For the data collection, we created a codebook, as recommended in the SQLR procedure (Pickering & Byrne, 2014; Pickering et al., 2015). We aimed to collect all information from the eligible papers relevant to meeting our goals with this codebook. The first author created a draft version of the codebook based on what information

**Figure 1**

PRISMA flow diagram summarizing the study selection process.

would be relevant to extract from the papers to answer the research questions. For an initial quality assessment, the first, second, and sixth authors then coded a random selection of papers (ten, five, and five, respectively), commenting on possible improvements to the codebook. Next, the first and third authors coded a random 10% of papers from the proceedings of CHI '17 to CHI '20 ($n = 72$, initial sample collected before we decided to focus on the years 2019 to 2022 and before refining our search query to the final version used) to check the quality of the codebook and calculate the overall inter-rater reliability (IRR) of the codings. The IRR for the inclusion criteria (Cohen's Kappa: $M = 0.926$, $min. = 0.838$, $max. = 1$) were almost perfect (Landis & Koch, 1977), and the overall average IRR (Cohen's Kappa: $M = 0.803$) was substantial (Landis & Koch, 1977). Calculations for all IRRs can be found in the OSF repository. In addition, the first and third authors discussed all disagreements in coding to settle on a final version of the codebook. For the final coding, all 153 records identified through the final search were split up between and coded by the first, second, third, and fourth authors. In total, we assessed 153 full papers for eligibility using our three criteria and coded all relevant information from 60 eligible papers. In addition, the sixth author

read through all 60 eligible records for detailed coding of the measured constructs. Thus, each eligible record was coded by at least two authors. Each record's methods section, paper title, and abstract were always read in full detail. At the same time, additional sections, such as the results, were screened using keywords (e.g., the names of scales identified) or fully read as was deemed necessary for answering our research questions. Hard-to-code cases were marked in the codebook and then discussed in regular meetings. Before a new coder started coding, they coded a random subset of five papers out of the 10% subset used for IRR calculation to ensure that the new coder would not deviate from the codings of the first and third authors. The final filled-out version of the codebook can be found on OSF.

Data coding and analysis

For each of the 60 eligible papers, we coded all scales used within the paper and what constructs were reported to be measured with both cited and self-developed scales. We categorized scales as either "cited" or "self-developed." We did not opt for terms such as validated scale, as this would require us to investigate secondary sources of scale validity. Therefore, survey scales were categorized as cited scales in our data when researchers provided any source for the scale, while self-developed scales did not provide a source. We further coded if the authors provided any items for the survey scales used, provided a rationale for using a particular scale, and reported evidence of the scale's psychometric quality. Additional outcomes included types of data collected (qualitative, self-reported quantitative, behavioral) and if authors reported adapting cited scales. An example of a code would be as follows: *Scale 1 adapted (1/0): did the authors mention adapting the scale in any way (e.g., removing items, rewording items, etc.)*. Refer to the OSF repository for a criterion catalog with explanations for all codes as part of the codebook.

To analyze the data, we created descriptive summary values, figures, and tables using formulas in the codebook (on Google Sheets) and the statistical software R (R Core Team, 2019, version 4.3.0). Key findings are reported in the following section. The

complete codebook and the R-script are available on OSF.

Results

We assessed a total of 153 full-text articles for eligibility, out of which we deemed 93 entries (60.78%) non-eligible, either because they were not an empirical study of UX interaction ($n = 15$ or 9.80%) or did not use a scale to study UX ($n = 78$ or 50.98%). A total of 60 papers remained for the analysis (39.22%).

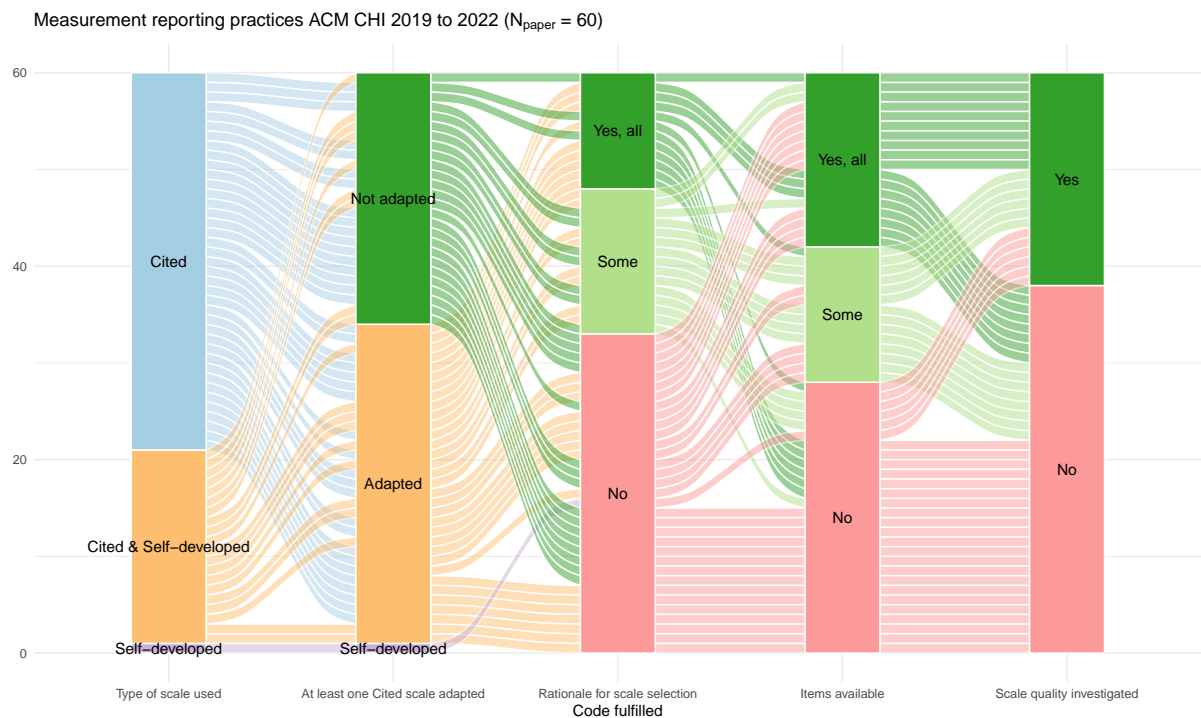


Figure 2

Alluvial plot summarizing frequencies of key measurement practices with survey scales in UX research papers in the proceedings of CHI '19 to '22.

Cited scales used

First, we present results regarding the scales identified through the review. Whenever a paper reported using a specific scale for the first time, we added that cited scale to our codebook. Whenever another paper reported using that same scale, we added an instance of measurement to that cited scale. Throughout the 60 eligible papers, we recorded 85 distinct cited scales and 155 instances of measurement where a

paper reported using one of those cited scales. For example, one of those 85 scales, the System Usability Scale, was used 14 times across all eligible papers (14 out of 155 instances of measurement). Most cited scales were only employed in one paper (mode = 1; min. = 1; max. = 14), with an average of 1.82 mentions per scale. More specifically, out of the 85 different cited scales, 60 were recorded once (70.59%). On average, authors reported using 1.05 different cited scales in their paper, with a mode of one cited scale used per paper (min. = 0; max. = 8). Across all 155 instances where a paper contained reports of one of the 85 cited scales, the System Usability Scale (SUS, Brooke, 1996) was most frequent with 14 instances of measurement (9.03%), followed by 13 instances for the User Experience Questionnaire (UEQ, Laugwitz et al., 2008, 8.39%), 12 for the NASA Task Load Index (NASA-TLX, Hart & Staveland, 1988, 7.74%), and five instances of measurement coded for the USE questionnaire (USE, Lund, 2001, 3.23%). A summary of the ten most frequently used cited scales is presented in Table 1, and the supplementary materials on OSF contain the complete list of coded scales.

Types of scales used: self-developed or cited

Next, we report the types of survey scales used in the eligible articles and how often cited scales were employed compared to self-developed scales. Across all 60 papers examined, 21 reported using self-developed scales for measurement (35.00%), with one article reporting the development of a new survey scale (1.67%). In comparison, 59 of 60 eligible papers reported utilizing at least one cited scale for measurement (98.33%). Of the 60 eligible papers, 39 reported using only cited scales (65.00%), followed by 20 using a mix of cited and self-developed scales (33.33%). One eligible paper reported using exclusively self-developed scales (1.67%). Figure 2 also depicts this distribution of types of scales across eligible papers.

Adaption of cited scales

Subsequent coding focused on whether authors reported adapting a cited scale for their work, that is, whether they made changes to the original scale, such as removing certain items or rewording them. Of the 155 instances of measurement where

Table 1

Top ten of the most frequently used cited scales in UX research published at CHI '19 - '22, identified in the literature review. Across 60 eligible papers, 85 different scales were used for a total of 155 uses.

Coded scale name	Source	Frequency
SUS (System Usability Scale)	Brooke (1996)	14 (9.03%)
UEQ (User Experience Questionnaire)	Laugwitz et al. (2008)	13 (8.39%)
NASA-TLX (NASA-Task Load Index)	Hart (2006) and Hart and Staveland (1988)	12 (7.74%)
USE questionnaire	Lund (2001)	5 (3.23%)
12-item Power user scale	Sundar and Marathe (2010)	3 (1.94%)
AttrakDiff	Hassenzahl et al. (2003)	3 (1.94%)
IMI (Intrinsic Motivation Inventory)	McAuley et al. (1989)	3 (1.94%)
IPQ (igroup presence questionnaire)	Schubert et al. (2001)	3 (1.94%)
Trust between People and Automation Scale	Jian et al. (2000)	3 (1.94%)
Presence Questionnaire (Witmer and Singer)	Witmer and Singer (1998)	3 (1.94%)
PXI (Player Experience Inventory)	Abeelee et al. (2020)	3 (1.94%)
SAM (Self-Assessment Manikin)	Bradley and Lang (1994)	3 (1.94%)
UX of the Recommender System	Knijnenburg et al. (2012)	3 (1.94%)

Note: Different scale versions (e.g., short and long versions) were combined for the UEQ, AttrakDiff, IMI, Big Five Inventory (John et al., 1991), and PANAS (Watson et al., 1988).

papers reported using a cited scale, 53 (34.19%) stated that the cited scale was adapted. Looking at this from the paper level, we see that 33 out of all 60 eligible papers (55.00%) reported adapting at least one cited scale. This rate of adaption can also be seen in Figure 2. Examples of adaptations included rewording items to fit the study, omitting items deemed irrelevant to the study, or utilizing only specific subscales considered essential to the study context.

Constructs investigated

For each eligible paper, we coded what constructs were measured using scales (both cited and self-developed). We consulted the information provided in both the methods and results sections of papers while mainly extracting the wording used for

constructs when reporting on the measured results (i.e., terms used for variable names). A construct was only coded once for each paper (i.e., if a construct was measured more than once in a paper, it was counted just the first time it was measured). We coded 172 distinct constructs across 412 instances where a construct was measured. For example, the distinct construct usability (1/172) was coded 14 times across all eligible papers (14/412). Across all eligible papers, we recorded an average of 5.28 different constructs per paper (mode = 1; min. = 1; max. = 19). Most constructs were only mentioned once (114 out of 172 or 66.28%), with the average mention per construct being 2.40 times (mode = 1; min. = 1; max. = 14). Among all constructs, usability was the most popular construct, studied 14 times (3.40% of the 412 instances of measurement), followed by attractiveness (12 out of 412 or 2.91%), effort (12 or 2.91%), presence (12 or 2.91%), enjoyment (9 or 2.18%), trust (9 or 2.18%), and user experience (9 or 2.18%). Table 2 shows the top ten constructs measured within the sample. In addition, we also looked at which scales were used to measure the most common constructs, which is also summarized in the table.

Furthermore, we looked at the co-occurrence of constructs to further understand which constructs researchers consider relevant when studying users' experiences. However, these results are influenced by the constructs measured with subscales of frequently used survey scales, such as the UEQ and NASA-TLX. The network diagram in Figure 3 illustrates the constructs that have been studied at least twice, and it indicates that constructs related to workload (e.g., mental demand, physical demand, effort) are commonly measured together. This is because authors often use individual items of the NASA-TLX to investigate several workload-related constructs. A similar trend is observed with constructs measured using subscales of the UEQ, such as novelty, perspicuity, and attractiveness. In the coded papers, attractiveness was the most central construct, requiring the fewest steps to reach other constructs. The constructs of satisfaction and trust connect several constructs related to the Technology Acceptance Model (Davis et al., 1989) (i.e., ease of use, usefulness, effectiveness) to constructs related to workload and attractiveness. Constructs related to need satisfaction (i.e.,

Table 2

Top 10 constructs of UX measured at ACM CHI and the scales used to measure them. We coded a total number of 172 unique constructs, with 412 combined instances where a construct was measured. Note that the list contains more than ten constructs because several were tied for the tenth spot.

Coded construct term	Frequency	Top scale(s) used to measure construct	Times used
usability	14 (3.40%)	SUS (System Usability Scale)	13
attractiveness	12 (2.91%)	UEQ (User Experience Questionnaire)	9
		AttrakDiff	3
effort	12 (2.91%)	NASA-TLX (NASA-Task Load Index)	8
presence	12 (2.91%)	IPQ (igroup presence questionnaire)	6
enjoyment	9 (2.18%)	seven different scales, all used 1-2 times	1-2
trust	9 (2.18%)	Trust between People and Automation Scale	3
user experience	9 (2.18%)	UEQ (User Experience Questionnaire)	6
efficiency	8 (1.94%)	UEQ (User Experience Questionnaire)	6
frustration	8 (1.94%)	NASA-TLX (NASA-Task Load Index)	8
mental demand	8 (1.94%)	NASA-TLX (NASA-Task Load Index)	8
novelty	8 (1.94%)	UEQ (User Experience Questionnaire)	8
performance	8 (1.94%)	NASA-TLX (NASA-Task Load Index)	8
physical demand	8 (1.94%)	NASA-TLX (NASA-Task Load Index)	6
satisfaction	8 (1.94%)	six different scales, all used 1-2 times	1-2

Note: All scales used to measure constructs more than twice are listed.

competence and autonomy) similarly function as a bridge between user experience constructs and player experience constructs (e.g., challenge, pleasure, immersion).

Rationale for scale selection

Further coding concerned whether the authors provided a rationale for using a particular scale in their paper. Whenever a paper contained any reasoning on *why* a specific scale was chosen for the study (e.g., due to past evidence of a scale's psychometric quality), we coded that paper as providing a rationale for selecting that scale. We did not assess the appropriateness of the rationales but only coded if the

15 papers, no items were given (45.45%).

Investigation of scale quality

To analyze the frequency and type of psychometric quality evaluations of scales, we coded several common types of quality investigation and the general question of whether authors reported any quality investigation of the scales used. Twenty-two out of all 60 eligible papers contained reporting on any form of quality investigation for the scales used (36.67%), as can also be seen in Figure 2. Among all coded indicators of scale quality, the reliability indicator coefficient alpha was reported most often (20 or 33.33%). One paper reported coefficient omega (1.67%). Concerning evidence for validity, two papers reported an EFA (3.33%), and four papers reported a CFA (6.67%). Six papers reported additional quality investigation methods (10.00%), such as correlations with other scales, correlations between sub-scales, or principal component analysis. Out of those 33 papers where at least one adaption of a cited scale was reported, 21 (63.64%) did not contain any reports on efforts of quality investigation.

Types of data gathered

To examine the types of data researchers collect in studies where survey scales are used, we considered three types of data: qualitative, self-reported quantitative, and behavioral quantitative. Because we looked at articles using survey scales for measurement, it is not surprising that all 60 articles reported collecting self-reported quantitative data of any kind. Among those articles, 41 also reported qualitative data (68.33%), while 43 contained behavioral data (71.67%). Looking at the types of data collected alongside each other, around half of all papers gathered a mix of all three coded data types (31 or 51.67%). Ten papers collected self-reported quantitative alongside qualitative data (16.67%), while 12 papers collected self-reported quantitative data concurrently with behavioral data (20.00%). Seven papers (11.67%) relied on self-reported quantitative data alone.

Discussion

We have presented results from a literature review covering four years of CHI proceedings (2019 to 2022). The sample, consisting of 153 initially screened and 60 eligible final records, was analyzed to better understand how current UX research uses survey scales and what constructs are measured using survey scales. From this, we derive not only what is measured in UX research but also how well UX research currently follows best practices when employing survey scales and if UX research is at risk of QMPs that threaten the validity of research findings and conclusions. In general, our literature review has provided several clear indicators of QMPs in UX research when survey scales are used. The following section will discuss these results and highlight their implications for scale-based UX research. Finally, we provide recommendations for researchers using scales for measurement, containing accessible information on best practices from fields related to UX research to help future work avoid QMPs.

Current practice in UX research using scales

We use the following section to compare our review's findings with the best practices summarized in the related work. Through this, we provide several indicators of current practice in UX research using scales, showing where best practices are followed or neglected and highlighting where scale-based UX research is at risk of QMPs.

Scales used

We identified 85 different cited scales, with the majority used only once (70.59%). Such limited common ground regarding the scales used aligns with past findings from Pettersson et al. (2018), where 40% of articles examined used a unique method. Nevertheless, 25 scales from our sample were used more than once (29.41%). The SUS (9.03%) and the NASA-TLX (7.74%) were the first and third most frequently used among all scales. Again, this finding is comparable to past research (Pettersson et al., 2018), where the NASA-TLX and the SUS were among the most commonly used scales. The second most used scale from our sample, the UEQ (8.39%), was not

identified to be used as often in past research (Pettersson et al., 2018). Instead, Pettersson et al. (2018) reported that the AttrakDiff (Hassenzahl et al., 2003) was the second most popular scale in their sample. In our study, the AttrakDiff ranked sixth among the most recurring scales, as it was only coded three times. Given that both scales build on the same theoretical model of UX (Hassenzahl, 2001), our results suggest that the newer UEQ has replaced the AttrakDiff (Hassenzahl, 2001), which is in line with recent findings by Díaz-Oreiro et al. (2021).

Constructs measured

In our systematic analysis, certain constructs were frequently measured, some of which with the same scale (e.g., "usability" with the SUS in 92.86% of cases). However, many constructs were measured just once (66.28%). The results thus indicate just a few established constructs in UX research. In this regard, for the three most frequently measured constructs, "usability," "attractiveness," and "effort," researchers repeatedly used the same scale (the SUS, UEQ, and the NASA-TLX, respectively). Furthermore, most top constructs were measured with the same two scales (i.e., the UEQ and NASA-TLX). This shows how closely related the scales and some of the constructs frequently measured in UX research are, something also reflected in Figure 3. In comparison, the picture is less clear for other constructs, such as "enjoyment," where multiple scales were used just once or twice, providing little evidence for any shared terminology or common acceptance of specific scales. This suggests that UX researchers share agreement on what scales to use when measuring classical usability constructs (i.e., "usability," "workload"), while such consensus is lacking in regard to other constructs. Our results further suggest that UX research is still heavily influenced by usability research while having difficulty reaching common ground on what constructs are essential to UX beyond usability. The low agreement among UX researchers on what specific scales to use for particular constructs is concerning, considering that repeated use of the same survey scales brings a key benefit: comparability of results across research. If UX researchers do not share common ground on what scales to use for the same constructs across studies, results can only be compared with limited

confidence. This diminished comparability confounds UX research because researchers cannot separate variations in findings introduced by a difference in methods (e.g., using various scales for the same construct) from actual differences relevant to the research focus (e.g., differences caused by experimental manipulations). Finally, the popularity of measuring constructs such as "user experience" and "usability" as distinct constructs may pose additional risks to UX research, given that they can be considered "umbrella constructs." Such constructs tend to be very broad concepts with little agreement among researchers on how to define or measure them, thus complicating the communication and accumulation of knowledge in HCI research (see Tractinsky, 2018, for a detailed discussion).

Types of scales used

Our review revealed that the majority of papers relied on cited scales only (65.00%), while around a third of articles reported using a mix of self-developed and cited scales. These results stand in contrast to what was reported in previous investigations. Both Bargas-Avila and Hornbæk (2011) and Pettersson et al. (2018) found an apparent over-reliance on self-developed scales compared to standardized scales. This discrepancy suggests that UX research has learned from past oversights, relying less on self-developed scales. However, in contrast to previous work, we strictly defined what is and is not a survey scale. In addition, we refrained from talking about standardized and validated scales, opting for the term "cited scales" instead. Thus, while our criterion for a scale to be classified as such arguably was harsher, the bar for a scale to be classified as not self-developed was likely lower. Unfortunately, a complete comparison of our results with past research is not possible because neither Bargas-Avila and Hornbæk (2011) nor Pettersson et al. (2018) provided details on what exactly they understood as "standardized," "validated," or "self-developed" scales. We conclude that UX researchers frequently cite a source when employing a survey scale. However, such a citation alone is insufficient proof of a scale's quality, leaving UX research vulnerable to QMPs, if additional best practices are neglected.

High rate of adaption

As stated in the related work, scale adaptations can affect the scale's quality (Flake & Fried, 2020; Furr, 2011; Juniper, 2009). Survey scales are ideally created with great rigor in a designated study, which gives them many advantages compared to self-developed scales often constructed without such consideration (Nunnally, 1978). If one adapts a survey scale, these advantages can be lost (Furr, 2011; Juniper, 2009). Within our sample, we observed that UX researchers frequently adapt cited scales. While most articles in our sample used at least one cited scale, these cited scales were adapted in over a third of all cases (34.19%). These results are consistent with recent findings from PX research, where 38.71% of articles reported on adapting the cited scale used (Aeschbach et al., 2021). Such adaptations raise the question of whether the cited scales retain their original quality and still measure what they were initially designed to measure (Furr, 2011). While some adaptations are justifiable (e.g., adapting the wording of items to the study context), they need to be transparently reported, so readers and reviewers can judge their legitimacy. This includes clear reasoning for those adaptations. In addition, the quality of survey scales needs to be re-investigated whenever they are adapted (Furr, 2011). Such re-investigation was rare in our sample, with two-thirds (63.64%) of papers reporting on an adaption not containing results from any quality re-investigation. Besides potentially affecting the quality of a scale, adaptations also reduce the comparability of survey scale results across papers (Flake & Fried, 2020). This further results in difficulty for the UX research field to work towards generalizable findings over many studies.

Lack of rationales for scale selection

When scales are used, selecting an appropriate scale to measure a particular construct is essential in research. Not providing a rationale for choosing a scale makes it difficult for readers and reviewers to make an informed judgment about the appropriateness of a scale for the research at hand. It also makes it hard to determine whether the scale was carefully developed or merely consists of self-developed items

taken from previous research (Aeschbach et al., 2021). While not providing a rationale for measurement selection does not mean that no such thought process has taken place (Ekkekakis & Russell, 2013), a lack of transparently reporting such a rationale leaves readers and reviewers in the dark (Flake & Fried, 2020). Therefore, researchers need to provide their rationale for choosing a particular scale. However, the results show that many papers do not provide a rationale for any scales used (55.00%), with only a fraction of all articles providing a complete rationale for all scales (20.00%). These findings are consistent with recent results from PX research, where only 19.05% of scale choices had a reported rationale (Aeschbach et al., 2021). Despite the rarity of rationales, there were instances where authors provided a good rationale for choosing a scale, such as the following for the UEQ: *"The User Experience Questionnaire (UEQ) [20] was chosen to assess the attractiveness and perceived novelty of the different conditions. We relied on the UEQ novelty scale to assess perceived novelty, an approach that has been mentioned before to investigate the impact of novelty in HCI research [19]. The UEQ has been found to show high convergent validity, and the reliability (Cronbach's alpha) ranges from acceptable to good [20]."* (Rutten & Geerts, 2020, p. 539). In this example, the authors clearly stated which constructs they measured with the UEQ and why they measured these constructs. In addition, they provided a source for why they relied on the scale to measure the construct "novelty" and cited evidence for the psychometric quality of the UEQ.

Nontransparent reporting of scale items

As mentioned in the related work section, providing all items used during research can help increase transparency and allow readers to assess the methods' adequacy. The results show that providing all items is not common in UX research. Almost half of all papers (46.67%) failed to fulfill the criterion of providing at least some items for the scales used. Results paint a similar picture concerning articles where an adaption to a cited scale was reported. This is in line with past UX research, where it was found that 51% of studies used self-developed scales without reporting any items (Bargas-Avila & Hornbæk, 2011). Findings thus suggest that UX research lacks

transparency regarding the scale items used. Such opaqueness regarding the items of a scale can hide many QMPs (Flake & Fried, 2020), thus causing several issues for UX research that need to be addressed. It is not uncommon for survey scales to exist in different versions. For example, both the UEQ and its short version, the UEQ-S, were reportedly used within our sample. In addition, there often are various language versions of the same scale (e.g., the UEQ is available in more than 30 languages according to the official website for the UEQ, <https://www.ueq-online.org/>, accessed on May 26, 2023). Each scale version has distinct psychometric properties, possibly delivering different results. If authors of a study do not clarify which exact items they worked with, readers cannot judge which version of a scale was used, if or how items were adapted, and how adequate the items were for the overall research effort. In addition, replication attempts are also hindered when items are not shared (Wacharamanotham et al., 2020), and the comparability of results across research is threatened (Flake & Fried, 2020).

Low rate of quality investigation

A survey scale's psychometric quality needs to be re-evaluated whenever a scale is used in a study (Furr, 2011). As the related work section mentioned, researchers should calculate and report evidence for a scale's reliability (e.g., coefficient alpha and omega) and validity (e.g., EFA and CFA). Survey scales are situated in their initial development and current context of use (Cairns & Power, 2018). Aside from a direct replication, both contexts have a distinct sample and a specific study setting. A scale's psychometric properties cannot be assumed equal across samples (Furr, 2011). Therefore, researchers should re-investigate the scale quality in a new research context to acknowledge these contextual limitations. Furthermore, whenever a scale is adapted, it is unclear if the adaption affects its quality (Flake & Fried, 2020; Furr, 2011; Juniper, 2009). Therefore, researchers adapting a scale always need to investigate the quality of their adapted version (Furr, 2011). In most papers from our sample, not even basic scale reliability or validity indicators were calculated, with only 36.67% reporting on any quality investigation. In addition, the finding that coefficient alpha was reported

most often (33.33% across all papers) is concerning, considering that coefficient alpha has seen heavy criticism in the past and is regarded as insufficient evidence for a scale's quality (Dunn et al., 2014). In our sample, only one paper (Bowman et al., 2021) reported coefficient omega while explicitly acknowledging its advantages over coefficient alpha. This finding suggests that many UX researchers are unaware of current practices within psychometrics, likely due to a lack of training and knowledge about best practices, exposing UX research to QMPs. Such an explanation would align with concerns raised in Law et al. (2014) regarding a need for enhanced training and education on measurement in UX research.

Concerning those papers that explicitly stated adapting a scale, the rate of quality investigation is comparably low (36.36%). These findings show that scales are frequently used in UX research without re-investigating the scale's quality. Without such re-investigations, researchers can not be sure that the scale performed as expected in their study setting, especially if adapted, jeopardizing the confidence in the data gathered with those scales. However, there were also positive examples in the sample where such investigations were reported: One eligible paper (Zhu et al., 2022) calculated coefficient alpha and an EFA after translating a scale and adapting it to the study context to ensure that the scale still performed as expected. A second eligible paper (Li & Caine, 2022) performed a CFA to ensure that the measures they used for a construct were consistent with their understanding of that construct. These two examples show that it is reasonable to expect UX researchers to investigate the quality of their scales, especially after adapting them to the study context. If reviewers and readers expected the reporting of such quality re-investigations in cases where scales were used in UX research, it would be one step towards improved measurement practices in UX research.

Types of data gathered

When investigating what types of data researchers gathered, a positive observation is that method triangulation is common in scale-based UX research. Among the eligible papers, the majority used at least two different data types alongside each other, with only 11.67% relying on self-reported quantitative data alone. Compared to

recent findings from UX research, where 46% of papers collected qualitative and quantitative data (Pettersson et al., 2018), we see that 68.33% of studies in the sample collected qualitative data in addition to collecting quantitative data using scales. Therefore, mixed-method approaches appear to be at least as prevalent in UX research using scales as in UX research in general. These results show that while UX researchers frequently use survey scales for measurement, they rarely rely on scales as the sole method for data collection. Survey scales, thus, are a frequent part of method triangulation within UX research, serving as one source of data alongside others, allowing researchers to leverage the individual advantages of each method. Therefore, if UX research frequently relies on data gathered using survey scales, proper use of this method needs to be given the same amount of attention and rigor as other methods used within UX research.

Questionable measurement practices: a threat to UX research

Based on the results, we conclude that UX research is at risk of QMPs because best practices are frequently neglected. Across all papers using any type of scale (cited, self-developed, or both), we found just one (Lan et al., 2022) that followed all appropriate best practices (either not adapting or using only self-developed scales, giving a rationale for all scales, providing all items, and investigating scale quality). Although the fact that just one article fulfilled all best practice criteria appears surprising at first, we want to emphasize that a substantial part of QMPs comes down to nontransparent reporting (Flake & Fried, 2020). In our review, we coded whatever information the authors provided in their papers. It is reasonable to assume that authors sometimes performed certain best practices during the measurement process (e.g., choosing a specific scale based on a rationale) but did not report on it. Therefore, the best practice criteria considered here are relatively strict when aggregated, thus painting a precarious picture. With improved reporting practices, many of these issues could be addressed or at least mitigated, which would considerably improve measurement practices in UX research.

Recent efforts toward open science in HCI, such as fostering greater transparency and sharing of materials (Wacharamanotham et al., 2020), or calls to preregister CHI experiments (Cockburn et al., 2018), have laid the groundwork for research that produces robust findings by making research more reproducible and replicable, mitigating questionable research practices. However, QMPs also threaten the validity of scientific research. They decrease trust in both the data gathered and the conclusions of a study as a whole (Flake & Fried, 2020). Proper use of survey scales and improved reporting thus is of utmost importance for the field of UX research, given the wide-spread use of such scales for measurement (Bargas-Avila & Hornbæk, 2011; Pettersson et al., 2018). Furthermore, greater agreement on what scales to measure with and what terminology to use for the constructs measured would help make UX research more comparable across papers, promoting theory-building in the UX field. Our literature review has shown that adherence to best practices needs to be improved, and reporting in scale-based UX research needs to be more transparent. To mitigate future QMPs in UX research, we provide recommendations in the following section on how to use survey scales in adherence to best practices and what to report on if scales were employed as part of a study.

Recommendations for improved measurement practices in UX research

Motivated by the problems identified in this literature review, we present six steps researchers should take when measuring constructs using scales for improved measurement and reporting practices in scale-based UX research. Our recommendations build on previous work by Flake and Fried (2020) and Aeschbach et al. (2021).

Step 1: decide if the research question requires scales

First, researchers need to evaluate whether measurement with survey scales is appropriate. This choice of method needs to be based on the research question or the problem investigated (Greenberg & Buxton, 2008). If the contribution to HCI is theoretical (e.g., new models or frameworks) or an artifact (e.g., a new system or technique), it may not be necessary to employ empirical studies using survey scales

(Wobbrock & Kientz, 2016). When the research question does not require scales, it is better not to use them at all than to misuse them.

Step 2: define the measured construct

Clearly defining all constructs of interest is essential because poor definitions threaten the validity of a study on multiple levels, from the validity of the scale to the validity of the findings beyond the study context (MacKenzie, 2003). In addition, being transparent about the definitions of constructs and the rationale for why researchers selected specific measures is crucial in preventing misunderstandings regarding what the researchers wanted to measure with the scale (Flake & Fried, 2020). For this step, researchers need to review existing definitions from related research and commit to one, or—if not satisfied—write a new definition. MacKenzie (2003) lists four aspects of a good definition that can serve as a guide: *"Good definitions should (a) specify the construct's conceptual theme, (b) in unambiguous terms, (c) in a manner that is consistent with prior research, and that (d) clearly distinguishes it from related constructs. A good definition should also specify the extent to which values of the construct are expected to differ across cases, conditions, and time. Also, when the construct is conceptualized as being multidimensional, the relations between the subdimensions and the superordinate construct should be specified"* (MacKenzie, 2003, p. 325).

Step 3: select a scale that corresponds to the definition

Next, researchers should review scales that have already been used in UX research to measure the target construct, and then read the original paper(s) for the scale. Verify that the definitions and theory underlying the scale and its constructs match the definition, and be aware that by choosing a specific scale, an indirect commitment to its underlying theory is made (DeVellis, 2017). Also, the researchers should consider existing evidence for the quality of a survey scale when making the choice (Flake & Fried, 2020). If the theory and definitions behind the chosen scale do not fit the research purpose, they should consider adapting the definition or searching for a scale that better serves the purpose. Standardized scales should be used wherever

possible (Hornbæk, 2006). If there is no suitable existing standardized scale, a new scale should be developed following best practices for scale development.

Step 4: implement the scale

Once the researchers have decided on a scale for the study, they need to implement it as closely as possible to the original. Be aware that even minor adaptations can change the quality of a scale (Juniper, 2009). Ensure the items are worded correctly and the scale format is correct (e.g., seven-point Likert-type scale). Adapt the scale only when necessary, and justify and record each adaptation. After data collection, form composite item scores by following the original author's instructions, if provided.

Step 5: calculate indicators of psychometric quality

Survey scales are limited by their initial development process and the context of use (Cairns & Power, 2018). Therefore, before analyzing the data gathered, researchers need to make sure that the scale meets certain quality criteria given the research context. If the sample size is sufficient, calculate both indicators for a scale's reliability (e.g., coefficients alpha and omega) and validity (e.g., EFA and CFA). At the very least, search for and report on past evidence for the scale's psychometric quality.

Step 6: transparently report the scale(s)

When writing up the research, researchers need to report on the entire measurement process, which followed the above steps, as transparently as possible. Report on relevant definitions and theories behind the scale(s) used. Explain the rationale for scale selection, including past evidence for scale quality, and give precise detail on how the scale(s) were implemented, including exact wording for all items. Furthermore, report any adaptations made, including justification, and report on evidence from the re-investigation into the quality of the scale(s) used. Providing all this information helps readers and reviewers reach an informed judgment of the methods' adequacy. It is also a crucial step toward preventing QMPs in future UX research. In addition, it helps other researchers in replicating the study.

Limitations

First, we only considered the CHI conference proceedings in our sample. CHI has been considered prototypical of the rest of HCI research (Hornbæk, 2006). Thus, our findings indicate how well UX researchers follow best practices when using survey scales for data collection. Nevertheless, other venues for UX research besides CHI arguably have different reporting standards and distinct research cultures, possibly leading to higher or lower adherence to best practices. Thus, comparisons with other venues for UX research would be an opportunity for future work.

Second, the results consider UX measurement from the perspective of published research and not of UX practitioners. Future work could explore the current industry practice on how survey scales are used in applied research by conducting interviews with practitioners or examining industry projects.

Third, our work focused on quantitative research using scales, not looking at qualitative UX research and other quantitative methods for gathering data. However, given that scales are among the most commonly used methods in UX research (Pettersson et al., 2018), our investigation provides valuable insights into a vital part of UX research. In addition, QMPs mainly pose a threat to scale-based research. Thus, an inquiry into other research methods was out of scope.

Future work

Future research could apply our approach to other venues besides CHI. Moreover, records for different years, both more distant and future, could be analyzed to search for additional indications of QMPs in UX research. In addition, definitions of constructs in UX research or statistical analyses of data collected with survey scales could also be investigated in future systematic reviews. These steps of the research process are also vulnerable to QMPs (Flake & Fried, 2020) but were out of this project's scope. Finally, future work could explore the most frequently used cited scales we identified in detail, investigating the validity of these scales, as was done in recent research from social and personality psychology (Flake et al., 2017; Hussey & Hughes, 2020).

Conclusions

This article reports a systematic quantitative literature review of four years of UX research published at CHI. We specifically examined how survey scales are used in UX research, which constructs are studied, and which scales are used to measure them. We investigated how frequently adherence to current best practices for using survey scales is reported in UX research papers. We considered a total of 153 articles from the proceedings of CHI '19 to '22 for eligibility screening, including 60 full-paper articles reporting empirical UX research using survey scales in the analysis. Results show that best practices are frequently neglected when using scales. Researchers rarely provide a complete rationale for choosing their scales (20.00%), often adapt scales (34.19%), and rarely report on investigations of scale quality (36.67%). In addition, transparency regarding the scale items used is lacking, with only a third of authors (30.00%) providing all items used in a study. Furthermore, results revealed 172 different constructs and 85 unique scales, alongside the fact that 70.59% of scales were only employed once, while 66.28% of constructs were only measured once. While this speaks to the diversity of scale-based UX research, it also comes with a risk of misunderstandings and limited agreement among UX researchers on *what* to measure and *how* to measure using survey scales, possibly hindering research progress. If current best practices are not adhered to, UX research risks questionable measurement practices that compromise the validity of the survey scales used, the findings of the respective studies, and scale-based UX research as a whole. To support the increased uptake of state-of-the-art psychometric practice, we recommend a six-step process for improved measurement in UX research. We hope to contribute to future UX research with these six steps by promoting more rigorous adherence to best practices when using scales. Through this, UX research can address concerns from adjacent fields regarding questionable measurement practices that threaten scale-based research's validity. In addition, we hope our recommendations will improve conditions for future UX research employing survey scales, promoting a deeper understanding of UX in general.

Data availability statement

All supplementary materials for this study are available on OSF (<https://osf.io/dgq6b/>).

Conflicts of interest

The authors declare no conflicting interests.

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