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The Emotional Flow Scale: Validating a Measure of Dynamic Emotional Experiences in Message Reception

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ABSTRACT
The dynamics of the emotional experience during message consumption, referred to as emotional flow, is hypothesized to be an important and influential element of message reception processes. In this article, we propose and validate a scale for measuring self-reported experiences of emotional flow following exposure to a message. Items were derived from Nabi and Green's initial theorizing and the final 6-item measurement model demonstrated good fit using data from seven studies ($N_{Total} = 2{,}626$). Measurement invariance tests supported the stability of the scale across written versus audio-visual narrative stimuli, participant sex and age, and two sample populations (student versus non-student). Finally, we present evidence of construct validity through an experimental study that manipulated and assessed emotional shifts during exposure to media content, where the scale was able to account for these emotional shifts. These findings suggest that the Emotional Flow Scale provides a valid instrument for measuring experiences of emotional flow.

Emotional flow refers to the experienced changes in one's emotions over the course of a media message (Nabi & Green, 2015; Nabi, 2015). The concept was first proposed by Nabi (2015) with a consideration of how shifts in emotion could be used to improve persuasive health messages. Nabi and Green (2015) extended these predictions to the context of narrative persuasion to propose that narratives may be especially well-suited to elicit emotional flow, as stories can activate strong emotions and emotional engagement (Green et al., 2012; Murphy et al., 2011; Oatley, 2003; Zillmann, 2006). Specifically, emotional flow is marked by the shifts in one's emotions over the course of a message. These shifts can involve changes from one discrete emotion to another, such as happiness to sadness, or changes in the intensity of a single emotion, such as mild happiness to extreme happiness. A greater number of such emotional shifts constitutes greater overall emotional flow. Notably, emotional flow is

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distinct from Csikszentmihalyi's (1990) psychological concept of *flow*, which refers to a mental state evoked by harmony in skill and task difficulty (Huskey et al., 2018; Nakamura & Csikszentmihalyi, 2014). In comparison, emotional flow describes changes in the emotional experiences during narratives or media messages more specifically. Emotional flow is also distinct from other related emotional concepts measured in media psychology research. For instance, *mixed affect* (Oliver & Bartsch, 2011) considers the experiences of several different emotions or emotions that conflict with one another during message reception. Similarly, Ott et al. (2021) conceptualized *emotional range* as a broader form of mixed affect, which involves the breadth of total affect experienced during message consumption (see also Watts & Slater, 2021). Emotional flow is unique from these concepts based on its temporal nature: Shifts occur over time between emotions or between different intensity levels of a single emotion.

Nabi and Green (2015) theorized that emotional flow is a key variable related to message selection and reception processes, and it is thought to predict several aspects of message processing and effects, including attention, engagement, and persuasion (see also Nabi, 2015). The importance of better understanding the emotional experiences in response to messages has been widely noted in media psychology research (e.g., Dunlop et al., 2008; Green & Brock, 2000; Knobloch-Westerwick et al., 2021; Moyer-Gusé, 2008; Oliver & Bartsch, 2011), and has implications across a variety of message reception and effects research including politics (Otto, 2018) and education (Titsworth et al., 2010). As such, validating a measure of the unique construct of emotional flow is an important step for testing the variety of outcomes believed to be affected by emotional flow, and advancing theories of media processing and effects. Although a growing number of studies have provided empirical evidence of the role of emotional flow in processes of communication (e.g., Alam & So, 2020; Clayton et al., 2021; Fitzgerald et al., 2020), these studies have varied in their approaches to measuring emotional flow.

For instance, Fitzgerald et al. (2020) developed a mathematical approach to calculate scores of emotional flow across segments of a message. Fitzgerald et al. (2020) paused viewers at a number of pre-determined points during the viewing process to survey their emotional experiences, then used formulae to compute emotional flow scores from the multiple measurements. Using a different approach, Alam and So (2020) measured emotional shifts by asking participants to report the emotional valence between the first and second half of a narrative. Ophir et al. (2021) conceptualized emotional flow as the emotional states expressed by the characters themselves (see also Sangalang et al., 2019), and recommended measuring emotional flow by evaluating multiple aspects including readers' perceptions of the characters' emotions and whether they experienced emotional shifts themselves. Finally, Clayton et al. (2021) used facial electromyography and changes in heart rate as indicators of negative and positive emotional changes throughout a message-viewing process. Although these approaches provide several ways to assess different elements of the emotional flow experience, they vary in their conceptualizations and measurement strategies. Thus, the findings cannot be directly compared. Furthermore, some of the previous measurement techniques are not easily applied across diverse message contexts. Such variety in measurement approaches makes it difficult to directly compare results across studies. Thus, the goal of the current article is to provide a practical, unified, and validated measurement strategy for the experience of emotional flow.

Current Research

In this article, we develop and validate a scale of emotional flow in response to media messages. We proposed a pool of items based on theorizing by Nabi and Green (2015) and engaged in selective item retention through a series of exploratory and confirmatory factor analyses. Using data from seven studies ($N_{\text{Total}} = 2{,}626$) in which participants read/viewed a media message and completed scale items regarding their emotional experience during exposure, we test the measurement model fit and assess invariance of the scale with regard to the narrative stimuli (written versus audio-visual), participant demographics (sex: male versus female; age: younger versus older), and sample type (student versus non-student). Finally, we present an experiment in which we manipulated shifts in emotion in response to media content and found that the scale could account for changes in emotional flow (defined by the number of manipulated emotional shifts) as hypothesized. The results of this study, as well as correlations between the scale and a series of narrative variables hypothesized to be associated with emotional flow, provide evidence of the scale's construct validity.

Method

Developing Scale Items

A total pool of 18 items was generated based on initial theorizing (Nabi & Green, 2015; Nabi, 2015; see Table 1) to assess the experience of emotional flow. The wording of scale items was reviewed and agreed upon by a team of graduate students and two professors with expertise in narrative and media research. Items were created to account for different aspects of emotional flow from both a discrete (e.g., "I felt negative emotions at times [e.g., sad, angry]) and dimensional (e.g., "Some of my emotions felt intense while others felt less intense") emotion perspective.

Table 1. Original Emotional Flow Scale Items.

Label	Full Items
Item 1	I experienced a lot of different emotions.
Item 2	**I felt a range of emotions.**
Item 3	If I had to list the emotions I felt [during the program], it would be a long list.
Item 4	I have trouble describing all the emotions I felt.
Item 5	I experienced strong emotions.
Item 6	**Some of my emotions felt intense while others felt less intense.**
Item 7	At points, [the program] felt emotionally intense.
Item 8	[The program] stirred complex emotions in me.
Item 9	**I felt negative emotions at times (e.g., sad, angry), while at other times I felt positive emotions (e.g., happy, thrilled).**
Item 10	I experienced both positive and negative emotions.
Item 11	I felt positive and negative emotions at *the same time*.
Item 12	**My feelings changed a lot from the beginning to the end of [the program].**
Item 13	[The program] played with my emotions.
Item 14	Sometimes I felt like laughing, sometimes I felt like crying.
Item 15	I was very emotionally engaged.
Item 16	**I felt a series of shifts in my emotions.**
Item 17	**I felt like I was on an emotional rollercoaster.**
Item 18	I was emotionally invested in the program.

Bold items indicate the items that were retained for the EFS.

Included Studies

We drew from data collected across seven studies including two university student samples ($n_{\text{Student}} = 254$), and five samples of participants from online research platforms (Mechanical Turk via TurkPrime [now CloudResearch; Litman et al., 2017], $n = 762$; ResearchMatch, $n = 1{,}610$; Total $n_{\text{Non-student}} = 2{,}372$). These studies were conducted to test separate hypotheses, and full results will be reported elsewhere. The focus of the current paper is only on the combined emotional flow results. The basic design was the same across all studies: Participants read or watched a narrative/media message and then responded to a series of questionnaires that included the emotional flow scale. The stimuli used across studies involved a variety of narratives and other communication messages presented in both audio-visual (A/V; $n = 1{,}124$) and written ($n = 1{,}502$) formats. The topics and themes of the stimuli also ranged across multiple domains of communication including entertainment, risk, and health messages. See Table 2 for descriptions of study designs and participant demographics; see also Appendix A in our online supplement for all stimulus material (https://osf.io/2jztm/?view_only=31e76da0b88e4bddad7caf75c1e7d3b5).

In addition to the emotional flow scale items, the studies included measures purported to be influenced by or related to emotional flow. We thus used these variables to evaluate the validity of the scale. These variables included narrative transportation (the state of mental and emotional immersion in a story world; Green & Brock, 2000), enjoyment (holistic responses related to fun or pleasure; Oliver & Bartsch, 2010), and appreciation (holistic responses related to poignancy and meaning-making; Oliver & Bartsch, 2010) of the stimuli. Transportation was measured using the Transportation Scale-Short Form (TS-SF; Appel et al., 2015). This scale uses a 7-point Likert-type response to items such as "I was mentally involved in the episode while [reading/watching] it" in which the item wording was altered to appropriately reflect the written or A/V stimuli (Cronbach's alpha ranged from $\alpha = .69$ to .86). Enjoyment and appreciation of the stimulus were measured using Oliver and Bartsch's (2010) enjoyment and appreciation scales. These measures use a 7-point Likert-type response scale in which participants rate the stimulus along three items for enjoyment ("fun," "a good time," and "entertaining;" Cronbach's alpha ranged from $\alpha = .77$ to .96) and three items for appreciation ("meaningful," "moving," "thought-provoking;" Cronbach's alpha ranged from $\alpha = .70$ to .87). For studies that assessed enjoyment/appreciation of separate stimulus clips (Study 1 and Study 3), we averaged across these responses to create general scores of enjoyment and appreciation. See Appendix B in the online supplement for the means, standard deviations, and reliabilities of the transportation, enjoyment, and appreciation scales.

Table 2. Individual Study Information.

Study (N)	Sample Origin	Stimulus Medium	Study Manipulation	Age	Sex
1 ($N = 96$)	US Students	A/V	Participants watched an episode of a crime drama manipulated to be emotionally consistent or contain emotional shifts.	$M = 20.19$, $SD = 2.33$ Min = 18, Max = 38	$n_{Female} = 52$ $n_{Male} = 44$
2 ($N = 511$)	ResearchMatch	A/V	Participants watched a short film after reading a prompt to elicit narrative enjoyment or appreciation.	$M = 52.20$, $SD = 16.08$ Min = 18, Max = 88	$n_{Female} = 366$ $n_{Male} = 142$
3 ($N = 517$)	CloudResearch	A/V	Participants watched a combination of three clips from two movies about dogs. Clip combinations were manipulated to elicit low, medium, or high levels of EF.	$M = 38.55$, $SD = 12.08$ Min = 18, Max = 78	$n_{Female} = 232$ $n_{Male} = 285$
4 ($N = 683$)	ResearchMatch	Written	Participants read a short story about a sniper following a prompt to elicit narrative enjoyment or appreciation.	$M = 53.29$, $SD = 15.86$ Min = 18, Max = 89	$n_{Female} = 519$ $n_{Male} = 161$
5 ($N = 158$)	US Students	Written	Participants read versions of a story about condom use that ended positively, negatively, or mixed.	$M = 20.14$, $SD = 2.21$ Min = 18, Max = 34	$n_{Female} = 86$ $n_{Male} = 72$
6 ($N = 416$)	ResearchMatch	Written	Participants read versions of a story about condom use that ended positively, negatively, or mixed positive.	$M = 51.41$, $SD = 16.81$ Min = 18, Max = 85	$n_{Female} = 313$ $n_{Male} = 103$
7 ($N = 245$)	CloudResearch	Written	Participants read versions of a story about organ donation, manipulated to elicit narrative enjoyment or appreciation.	$M = 42.97$, $SD = 14.04$ Min = 19, Max = 78	$n_{Female} = 154$ $n_{Male} = 91$

Data missing/not reported: Study 2: $n_{Age} = 9$, $n_{Sex} = 3$; Study 4: $n_{Age} = 10$, $n_{Sex} = 3$; Study 6: $n_{Age} = 4$.

Results

We began by conducting an exploratory factor analysis (EFA) on our 18 items to determine the number of factors that could be extracted from our data and how each scale item loaded on these factors. Next, we ran confirmatory factor analyses (CFA) to examine how the exploratory factor structure fit. We engaged in selective item retention to refine the fit of our measurement model and pare down the number of scale items. Once we established a satisfactory measurement model, we tested the measurement invariance of our scale across four distinct group splits. Finally, we evaluated the construct validity of our scale using experimental data provided by one of our studies (Study 3).

Exploratory Factor Analyses

To determine our initial factor structure, we performed an EFA on the total 18 scale items using principal axis factoring (PAF) with Oblimin rotation (Delta = 0) using combined data from Study 1 and Study 2 ($n = 607$). The factor extraction was unconstrained. The results demonstrated a Kaiser-Meyer-Olkin (KMO) index of .97 and Bartlett's test of sphericity was significant (Approx. Chi-Square [$df = 153$] = 9456.93, $p < .001$), demonstrating good sampling adequacy and that our scale items were suited for structure detection. The results of an initial unconstrained EFA with all 18 items suggested 2 factors. The first factor explained 59.66% of the variance in the data and the second factor explained an additional 5.59% of variance. However, based on the pattern matrix demonstrating that the majority of the 18 items loaded more strongly on the first identified factor compared to the second identified factor, the low additional variance explained by the second factor, and the visualization of the scree plot (which demonstrated a sharp bend after one factor), we interpreted that a single factor solution best fit the data. We therefore ran a second EFA constraining the factor extraction to 1 factor. Total variance explained was 59.39%. With regard to factor loadings, all items loaded above .60 with the exception of item 14 (.52). See Appendix C for the full list of factor loadings and corresponding scree plot.

Confirmatory Factor Analyses

We then tested our 18-item, single factor measurement model in IBM SPSS AMOS (Version 27) using maximum likelihood estimation. The CFA was conducted using the remaining data from Studies 3–7. The model did not fit the data well ($\chi^2 = 4850.91$, $p < .001$, RMSEA =.13 [Lower CI =.13, Upper CI =.14], CFI =.86, SRMR =.05). Therefore, we engaged in iterative selective item retention to refine the measurement model and attain good fit. Items were removed on the basis of poor face validity, low factor loadings, and modification indices of our CFA. From this process, we removed items 1, 3, 4, 5, 7, 8, 10, 11, 13, 14, 15, and 18 from our initial pool resulting in a 6-item, single factor measurement model. The 6-item model demonstrated both good fit ($\chi^2 = 114.34$, $p < .001$, RMSEA =.08 [Lower CI =.06, Upper CI =.09], CFI =.99, SRMR =.02; see cutoff criteria recommended by Hu & Bentler, 1999) and excellent reliability ($\alpha = .92$). See Table 3 for the final scale items, factor loadings of items using data from all seven studies, and fit indices by study. Given that a satisfactory measurement model was achieved, we then assessed the measurement invariance of our scale.

Assessing the Stability of the EFS Factor Structure

As a brief primer, measurement invariance is a statistical property that implies a latent construct is measured consistently across multiple populations or repeated measurements (see Kühne, 2013; Putnick & Bornstein, 2016). Measurement invariance is assessed by progressively constraining a measurement model to determine if the factor structure is stable across different groups of participants. After determining that a measurement model demonstrates acceptable fit through confirmatory factor analysis, one can begin testing for measurement invariance. The first step requires the researcher to divide their sample into mutually exclusive subgroups. Conceptually, this step is meant to separate different populations that may exist within the sample (e.g., sex, race, school, country), and by splitting the sample, one can test whether the proposed constructs are being measured consistently between the identified subgroups.

The second step involves determining which level of measurement invariance is achieved by the scale. Each level of invariance provides a more rigorous test of the measurement model, indicating whether specific components of the factor structure are equivalent across groups. The first level of invariance (e.g., *configural* or baseline invariance; for terminology, see Putnick & Bornstein, 2016) determines whether the proposed measurement model fits across all specified subgroups (i.e., multigroup confirmatory factor analysis). Configural invariance implies that the proposed pattern of latent variables and scale items (i.e., factor structure) operates consistently across different populations. The second level of invariance (e.g., *metric*, or weak invariance) holds the factor loadings of each observed variable equivalent. Metric invariance implies that the unit of measurement for each scale item is constant and that each scale item represents its latent construct to a similar degree across groups. The third level of invariance (e.g., *scalar*, or strong invariance) additionally holds the intercepts of the observed variables to be equivalent. Scalar invariance indicates that the unit of measurement (i.e., factor loadings) and baseline values (i.e., intercepts) of underlying latent constructs function similarly

Table 3. Scale Items, Factor Loadings, and Model Fit by Study for EFS.

Scale	Emotional Flow Scale Full Items	Loading
Item 1	I felt a range of emotions.	.86
Item 2	Some of my emotions felt intense while others felt less intense.	.80
Item 3	I felt negative emotions at times (e.g., sad, angry), while at other times I felt positive emotions (e.g., happy, thrilled).	.77
Item 4	My feelings changed a lot from the beginning to the end of [the program].	.77
Item 5	I felt a series of shifts in my emotions.	.90
Item 6	I felt like I was on an emotional rollercoaster.	.79

Model Fit	χ^2	*p*	RMSEA [LL, UL]	CFI	SRMR	α
Overall	127.53	<.001	.07 [.06, .08]	.99	.02	.93
Study 1	13.67	.135	.07 [.00, .15]	.98	.05	.78
Study 2	17.97	.036	.04 [.01, .17]	.99	.02	.89
Study 3	21.46	.011	.05 [.02, .08]	.99	.02	.87
Study 4	52.61	<.001	.08 [.06, .11]	.98	.02	.92
Study 5	18.90	.026	.08 [.03, .14]	.99	.02	.93
Study 6	63.90	<.001	.12 [.09, .15]	.96	.03	.91
Study 7	42.52	<.001	.12 [.09, .16]	.97	.03	.91

df = 9. All factor loadings are standardized and represent the factor loadings across data from all seven studies. LL and UL represent 90% confidence intervals around RMSEA estimates. We attribute high RMSEA values to the low degrees of freedom within the measurement model (see Kenny et al., 2015).

across groups. Thus, when scalar invariance is achieved, differences in the mean values of latent variables can be meaningfully compared and evaluated between groups. The fourth and final level of invariance (e.g., *residual*, or strict invariance) constraints the residual terms of each scale item. Residual invariance denotes that the amount of explained variance (i.e., squared multiple correlations) and random error (i.e., residual variance) for each item is consistent across groups. For a more in-depth discussion of each invariance level, see Wang et al. (2018).

Importantly, the models tested across the different levels of invariance are nested within one another. For example, when comparing metric invariance (the less restrictive test) to scalar invariance (the more restrictive test), metric invariance equates the factor loadings of each scale item while scalar invariance equates the factor loadings *and* intercepts of each scale item. Thus, the process of invariance testing involves first fitting a measurement model at the lowest level of invariance (e.g., configural) and determining which level of measurement invariance is achieved through a series of model comparison tests. In other words, if the model demonstrates no decrement in fit when transitioning to a more restrictive level of invariance (e.g., comparing scalar fit to metric fit), one can conclude that the scale is invariant at the higher level.

When comparing nested models, the χ^2 difference test has been the traditional metric for assessing decrement in fit. Despite its utility, scholars have identified that the χ^2 fit statistic is quite sensitive to large sample and model sizes (see Bentler & Bonett, 1980; Jöreskog & Sörbom, 1993). Consequently, χ^2 difference tests conducted between models with large samples or high degrees of freedom will likely be significant, regardless of whether a more restrictive factor structure demonstrates actual decrement in fit (Herzog et al., 2007). To remedy this issue, structural equation modeling researchers have recommended using alternative goodness-of-fit indices (ΔGFI) to evaluate change in model fit (for an overview; see Putnick & Bornstein, 2016; see also Cheung & Rensvold, 2002; Chen, 2007; Rutkowski & Svetina, 2014). Based on this body of work, the Δcomparative fit index (CFI), Δstandardized root mean square residual (SRMR), and ΔMcDonald's non-centrality index (Mc NCI) are recommended as the most useful alternatives for overcoming the limitations of χ^2 difference tests given these indices are robust to both large sample and model size (Putnick & Bornstein, 2016). Since the size of our sample is large ($N = 2{,}626$), we utilize these ΔGFI for our model comparison metrics, and follow the recommended cutoff criteria of $\Delta CFI \leq .01$, $\Delta SRMR \leq .015$, and $\Delta Mc\ NCI \leq .02$ (Chen, 2007; Cheung & Rensvold, 2002).

Measurement Invariance Tests

We tested measurement invariance across four distinct group comparisons (e.g., narrative stimulus, participant sex, participant age, and sample type). We used multiple binary group splits to provide a variety of tests that assess the robustness of our scale's measurement invariance. We selected some group comparisons based on the notion that they are potentially more central to the theory of emotional flow (i.e., the type of narrative medium), and we selected other group comparisons based on their frequent use in the measurement invariance literature (i.e., demographics). The full results of these invariance tests are presented in Table 4.

The first group comparison was based on the type of narrative stimulus. We compared participants who read a written narrative (n = 1,502) to those who watched an audio-visual narrative (n = 1,124). Using this group comparison, our scale demonstrated residual invariance. We note that this result is promising given both scalar and residual invariance are regarded as notably difficult thresholds to meet in the measurement invariance literature (van de Schoot et al., 2015).

The second group comparison was based on participant sex (assigned at birth): male (n = 898), female (n = 1,722). Six participants were excluded as they did not provide the sex they were assigned at birth. Using this group comparison, our scale again achieved residual invariance.

The third group comparison was based on the age of the participants. We conducted a binary split on the average age of the participants in our sample (M = 45.65). This split was determined by a natural separation of these groups identified in the data. Participants who were the age of 45 and younger were included in the younger group (n = 1,318) and participants who were the age of 46 and older were included in the older group (n = 1,285). Participants (n = 23) were excluded from this invariance test if they did not provide their age. Using this group comparison, we found that our scale again demonstrated residual invariance.

The final group comparison was based on the population that was used to sample data. We compared participants who were sampled from either a student (i.e., university; n = 254) or non-student population (i.e., Amazon's Mechanical Turk; n = 2,372). Using this group comparison, our scale demonstrated configural invariance and failed to achieve metric invariance. We conducted a series of partial metric invariance tests to examine whether removing the factor loading constraints on any of the items (i.e., allowing factor loadings of specific items to vary between groups) would remedy the decrement in fit of the metric model. By removing the factor loading constraint on Item 3 (i.e., "I felt negative emotions at times [e.g., sad, angry], while at other times I felt positive emotions ([e.g., happy, thrilled]"), the scale demonstrated no decrement in fit and thus achieved partial metric invariance ($\Delta\chi2$ = 3.50, Δdf = 4, p = .478, ΔCFI = .000, ΔSRMR = .016, ΔMc NCI =.000).

Table 4. Invariance tests of EFS.

	Model Fit						Model Comparison					
Invariance	χ^2	*df*	*p*	CFI	SRMR	Mc NCI	$\Delta\chi^2$	Δdf	*p*	ΔCFI	ΔSRMR	ΔMc NCI
Stimuli												
Configural	152.00	18	<.001	.988	.023	.975	-	-	-	-	-	-
Metric	182.82	23	<.001	.985	.024	.970	30.82	5	<.001	.003	.002	.005
Scalar	278.35	29	<.001	.977	.025	.954	95.53	6	<.001	.008	.001	.016
Residual	305.87	35	<.001	.975	.025	.950	27.51	6	<.001	.002	.000	.004
Sex												
Configural	134.85	18	<.001	.989	.019	.978	-	-	-	-	-	-
Metric	142.49	23	<.001	.989	.019	.977	7.65	5	.177	.000	.000	.001
Scalar	187.86	29	<.001	.986	.019	.970	45.37	6	<.001	.003	.000	.007
Residual	264.17	35	<.001	.979	.024	.957	76.31	6	<.001	.007	.005	.013
Age												
Configural	143.12	18	<.001	.988	.014	.976	-	-	-	-	-	-
Metric	169.46	23	<.001	.986	.017	.972	26.34	5	<.001	.002	.003	.004
Scalar	239.70	29	<.001	.980	.017	.961	70.25	6	<.001	.006	.000	.011
Residual	254.13	35	<.001	.980	.017	.959	14.43	6	.025	.000	.000	.002
Sample												
Configural	139.22	18	<.001	.989	.015	.977	-	-	-	-	-	-
Metric	166.84	23	<.001	.987	.041	.973	27.62	5	<.001	.002	.026	.003
Scalar	208.47	29	<.001	.984	.035	.966	41.63	6	<.001	.003	.006	.007
Residual	238.61	35	<.001	.982	.056	.962	30.13	6	<.001	.002	.021	.007

Cutoff criteria: ΔCFI ≤ .01, ΔSRMR ≤ .015, and ΔMc NCI ≤.02. Shaded cells indicate the levels of invariance that were not achieved by the scale.

Evaluating the Validity of the EFS

Given that we had established statistical validity using the invariance tests, we then assessed the construct validity of the scale. We did so using an experimental study designed to manipulate and assess shifts in emotion in response to media content (Study 3), as well as through a series of correlation analyses with theoretically relevant narrative variables (transportation, enjoyment, and appreciation).

Evidence of the EFS with Manipulated Emotional Flow

First, we sought to provide evidence that the scale is able to capture differences in experienced emotional flow that align with experimentally manipulated levels of emotional flow. In Study 3, participants were randomly assigned to one of three conditions manipulated to vary the number of emotional shifts elicited (*zero shifts*, *one shift*, or *two shifts*). Participants in each condition saw a series of three clips taken from the films *A Dog's Life* and *A Dog's Purpose*. Through pre-testing, six clips were identified, three of which elicited strong happiness and three of which elicited strong sadness. For example, a happy clip showed someone playing with their dog at the park, whereas a sad clip involved someone putting their dog down at the vet. For the manipulation of the level of emotional flow, each participant watched a series of three clips that were strategically ordered to elicit a target number of emotional shifts. An emotional shift constituted watching two clips back to back that were not emotionally consistent (i.e., watching a happy clip directly after a sad clip or watching a sad clip directly after a happy clip). Participants in the *zero shifts* condition saw a series of three clips that were consistent in emotion (happy-happy-happy or sad-sad-sad); participants in the *one shift* condition saw a series of three clips that were ordered to feature a single shift in emotion (happy-happy-sad, happy-sad-sad, sad-happy-happy, or sad-sad-happy); and participants in the *two shifts* condition saw a series of clips that were ordered to feature two emotional shifts (happy-sad-happy or sad-happy-sad).

As previously defined, emotional flow is marked by the shifts in one's emotions over the course of a message, with a greater number of such emotional shifts constituting greater overall emotional flow. As such, if the EFS is successfully capturing emotional flow, we would expect participants in the *zero shifts* condition to report the lowest EFS scores, participants in the *one shift* condition to report higher EFS score, and participants in the *two shifts* condition to report the highest EFS scores. To assess this prediction, we conducted a one-way ANOVA with linear contrast with EFS as the dependent variable and number of shifts as the independent variable. Levene's test indicated that the homogeneity of variance assumption was violated, $F(2, 514) = 16.88$, $p < .001$. Thus, we interpreted the contrast test which does not assume equal variances and utilized Games-Howell post hoc tests to examine differences between conditions. Results showed that the number of emotional shifts in the media presented to participants predicted their EFS scores in a linear fashion, $t(226.07) = 10.08$, $p < .001$. Post hoc testing further confirmed that each of the three conditions were significantly different from each of the others in the predicted manner, with *zero shifts* ($M = 3.67$; $SD = 1.51$) being significantly lower ($p < .001$) than both *one shift* ($M = 4.93$; $SD = 1.30$) and *two shifts* ($M = 5.25$, $SD = .95$) and the *one shift* condition being significantly lower than the *two shift* condition ($p = .019$). Taken together, these results provide initial evidence that the EFS is able to capture differences in emotional flow as intended. We note that a limitation of this study is that we only manipulated one type of emotional flow (valence). We recommend future studies continue to test the validity of the scale by using other types of emotional changes (e.g., changes in intensity, changes within the same valence).

Hypothesized Correlations of the EFS with Narrative Variables

We then evaluated validity of the scale through the relationships between emotional flow and theoretically related variables (transportation, enjoyment, and appreciation). See Table 5 for the corresponding correlation matrix. First, Nabi and Green (2015) hypothesized a positive association between emotional flow and transportation, as narratives that contain a higher degree of emotionality tend to be more transporting. Based on this proposition, our measures of emotional flow should be positively related to transportation (p. 139; see also Appel & Richter, 2010). Second, Nabi and Green hypothesized that emotional flow should be associated with enjoyment of the narrative (Nabi & Green, 2015, p. 149). Extending this theorizing to a similar positive narrative appraisal, appreciation, our emotional flow measures should be positively correlated with both enjoyment and appreciation.

As expected, the EFS positively correlated with transportation, enjoyment, and appreciation. Several interesting patterns emerged from the correlations that are worth noting. First, while the correlation between emotional flow and transportation was strong and significant ($r = .64$), it was not strong enough to assume that the two measures conceptually overlapped. A correlation of $r = .90$ might indicate that emotional flow and transportation are tapping into a similar or the same experience (Kline, 2016; see also Campbell & Fiske, 1959). Second, the correlations between enjoyment and emotional flow were consistently smaller than the correlations between emotional flow and appreciation. This pattern suggests that although emotional flow is positively associated with both forms of narrative appraisal, it is more closely aligned with appreciation responses. Future studies may investigate this pattern further to better understand the seemingly unique relationship between emotional flow and appreciation.

Table 5. Correlation Matrix Across all Studies.

	1.	2.	3.
1. EFS	–		
2. Transportation	.64**	–	
3. Enjoyment	.26**	.37**	–
4. Appreciation	.63**	.70**	.37**

*$p < .05$; **$p < .01$. $N = 2{,}626$. See Appendix D for correlation matrices by study.

Discussion

The purpose of this research was to develop and validate a scale of emotional flow following narrative or media message reception. Using data from seven samples, we provide evidence that the emotional flow scale (EFS) is a sound metric for measuring this experience. We tested for measurement invariance across multiple groups including narrative stimulus, participant sex and age, and student versus non-student sample type, and found that the scale operates similarly across these different groups. We further provide evidence of construct validity for the scale. First, in an experimental study (Study 3), we manipulated the number of emotional shifts over the course of a media message and found that the scale could significantly account for these changes. Second, through correlations with theoretically-related narrative variables including transportation, enjoyment, and appreciation, we find that the EFS is significantly associated with the narrative variables as hypothesized. These findings make important contributions to media psychology for unifying the research on media and narrative effects, as well as broader areas of communication research examining emotional variance in message reception.

Implications and Future Use of the Emotional Flow Scale

The validation of the EFS provides a method for measuring this experience that can unite current approaches to studying emotional flow. As discussed in the front end, there are a number of existing measurements that assess different aspects of the emotional flow experience (Alam & So, 2020; Clayton et al., 2021; Fitzgerald et al., 2020; Ophir et al., 2021). However, without a universal measure of emotional flow, researchers lack a shared means of assessing emotional changes during media and narrative exposure. We recommend future emotional flow research utilize the current scale to offer cross-study comparisons of the emotional flow experience.

In addition to providing a unified measure of emotional flow, a strength of this scale validation is that the scale items can account for both discrete and dimensional emotional approaches. The EFS can therefore be applied by future researchers who take either perspective. This feature of the scale may therefore help to unify research from these differing perspectives of emotion. Moreover, because our studies involved multiple communication contexts (entertainment, health, risk) and message mediums (written, A/V), we can conclude that the scale lends itself to a variety of communication research domains.

However, despite the benefits of this scale validation, some researchers might want to explore more nuance in the emotional flow processes, such as differences in the intensity of the emotional experience as compared to differences in emotional valence. Although the current scale includes items that tap into potential subdimensions of emotional flow (e.g., Item 1 relates to range in discrete emotions, Item 2 relates to changes in emotional intensity, and Item 3 relates to changes in emotional valence), the scale in general provides a valid metric of one's overall emotional flow experience. As such, potential subdimensions of emotional flow should be explored in future research. In the following section, we discuss the steps necessary in future attempts to develop a multi-dimensional emotional flow scale.

Conceptualizing Subdimensions of Emotional Flow

In addition to its use across a variety of messages and populations, the development of the EFS also helps to identify a future endeavor for researchers to differentiate separate emotional shift dimensions. In their initial theory piece, Nabi and Green (2015) describe different types of emotional shifts. We drew from this theorizing when creating the scale items, but a worthwhile goal for researchers would be to explore these different types of emotional change in more depth. A formalization of emotional flow subdimensions would add both conceptual and operational clarity to emotional flow theorizing and introduce several new directions for emotional flow research. We recommend three unique theoretical dimensions that capture distinct variance in the emotional flow experience: *diversity*, *intensity*, and *valence*.

First, in her initial theory piece, Nabi (2015) discussed the ways in which shifting between individual emotional states may facilitate the persuasion process (p. 115). Drawing on a discrete perspective of emotion, Nabi predicted that messages that facilitate changes in an individual's emotional state from one distinct state to another (e.g., from happiness to sadness) throughout message reception enhance message impact. Consistent with this conceptualization, we would consider emotional shifts between discrete emotions as a diversity subdimension of emotional flow, which we conceptually define as *variance in the number of discrete emotions experienced* (see also Nabi & Green, 2015, p. 143; Nabi, 2015, p. 117). Item 2 of the EFS ("I felt a range of emotions") corresponds to this subdimension.

Second, Nabi and Green (2015) proposed that "marked variation in the intensity of a specific emotional experience" can further constitute an emotional shift (p. 143). For instance, shifting from a mild to an extreme degree of the same emotion (e.g., from slight sadness to overwhelming grief), although not a change in the discrete emotion, is nonetheless a change in an individual's emotional state. Such changes are common to dynamic emotional experiences, such as when story structures build suspense to increasingly raise emotions or anticipation as the plot unfolds. Thus, we would propose a second subdimension of emotional flow intensity, which we conceptually define as *variance in the strength of an associated emotional state*. Item 6 of the EFS ("Some of my emotions felt intense while others felt less intense") corresponds to this subdimension.

Third, Nabi and Green (2015) further proposed that emotional shifts can involve changes in the valence of felt emotions, or shifting "from negative to positive (e.g., fear to relief)" or "from positive to negative (e.g., happiness to sadness)" (p. 143). We would distinguish emotional valence from emotional diversity such that shifts between emotional states (e.g., like those in emotional diversity) are a necessary but insufficient condition for capturing some emotional shifts. For instance, changing from anger to fear would constitute a shift in emotional diversity but not a shift in emotional valence, because both emotional states are negative. Thus, we would define the emotional valence subdimension as *variance in the extent to which an emotional state is positive or negative*. Item 9 of the EFS ("I felt negative emotions at times [e.g., sad, angry], while at other times I felt positive emotions [e.g., happy, thrilled]") corresponds to this subdimension.

Taken together, these subdimensions would formalize the descriptions of different types of emotional shifts proposed by Nabi and Green (2015) into measurable categories of emotional flow, and therefore could provide several new directions for future research. For instance, some researchers may be especially interested in shifts in emotional intensity, such as those investigating processes related to excitation transfer theory (Zillmann, 1983). A close sports match between rival teams may elicit a strong emotional shift from suspense to elation when the audience's favored team wins. Other researchers may be particularly interested in shifts in emotional valence and how they correspond with mixed emotionality (e.g., Oliver & Bartsch, 2011). For example, in the current study, we found that our scale correlated more strongly with appreciation than enjoyment. This finding could be attributed to the nature of the current stimuli and our focus on comparing emotions with opposing valences (e.g., the happy vs. sad manipulation provided in Study 3). In comparison, the sports example may elicit a stronger correlation with enjoyment compared to appreciation. Thus, there might be situations within entertainment media (both narratively based and non-narratively based) where our scale might vary more strongly with the experience of enjoyment rather than appreciation. An extended version of the current scale that measures the proposed subdimensions would be an effective approach to address these questions.

In addition to studies that examine the subdimensions independently, other research could assess the relationships between the dimensions. For instance, are some of the dimensions more or less important for the process of persuasion? Are some dimensions necessary for the co-occurrence of other dimensions? It could be that some dimensions are more representative of the core concept of emotional flow, whereas others account for additional variance in the emotional flow experience. Although our scale only begins to tap into these unique subdimensions, future research should continue to explore such emotional dynamics in message reception and effects. In particular, we recommend future researchers expand the total pool of items presented in the current study (see Table 1) to validate a multi-dimensional scale of emotional flow. This validation effort should include the creation of a large pool of more pointed items aimed at capturing the unique qualities of the proposed subdimensions. By validating subscales that capture the distinct qualities of these subdimensions, a multi-dimensional scale could help situate emotional flow within the nomological network of existing narrative engagement concepts.

Limitations

While this scale validation makes several contributions to narrative and media research, some limitations are worth noting. First, the scale only measures perceptions of emotional flow following exposure to the message. It does not directly measure the emotional experience during message exposure nor across multiple points. We do not see this as a flaw of the scale itself, as retrospective self-report scales are common and useful in media and narrative effects research. However, using additional measures of emotional flow alongside the emotional flow scale such as those discussed above could continue to strengthen our understanding of the concept.

A second limitation relates to the lack of a test for discriminant validity. The studies did not share a measure that would typically be used to evaluate discriminant validity, such as other psychological or media reception variables. However, in an effort to address this limitation, we examined how the scale correlated with participant age and sex, variables that have not been suggested as correlates of emotional flow. When examining associations between our scale and participant age and sex by study, we consistently find the correlations between these variables are non-significant (see Appendix D of our online supplement), which could be taken as an initial small step toward discriminant validity. Future studies should specifically include variables that can provide a better evaluation of the scale's discriminant validity.

Conclusion

As the interest in emotional flow research grows, it becomes increasingly important for researchers to utilize a shared way of measuring this experience. The current findings suggest that the emotional flow scale (EFS) is a reliable and valid instrument for measuring emotional flow in media and communication research. Given the strengths of the scale characteristics and its potential to unite cross-context study findings, we recommend that researchers use this scale to assess dynamic emotional experiences during message exposure.

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Data availability statement

The data described in this article are openly available in the Open Science Framework at https://osf.io/2jztm/?view_only=31e76da0b88e4bddad7caf75c1e7d3b5.

Open scholarship

This article has earned the Center for Open Science badges for Open Data and Open Materials through Open Practices Disclosure. The data and materials are openly accessible at https://osf.io/2jztm/?view_only=31e76da0b88e4bddad7caf75c1e7d3b5.

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