The Cautious Smile: Effects of Emoji Exposure on Risk-Taking

Eleanor Ng Wen Yi, Jared Lim Jie Rui, Tang Jadon, Tai-Sen He

ABSTRACT

Despite the widespread use of emojis in digital environments, little is known about their effect on economic decision-making. Using a between-subjects online experiment with 399 participants, we randomly assigned participants to view either a positive or neutral emoji across 30 lottery decision pages, with risk preferences elicited using a Multiple Price List method. We find that participants in the positive emoji condition selected significantly more safe choices on average, indicating greater risk aversion — a result robust across alternative sample restrictions and unlikely to reflect demand effects. The findings are more consistent with mood maintenance theory than the Affect Infusion Model, though a mediation analysis finds no evidence that affect, perceived probability, or relaxation explain the treatment effect. These results demonstrate that subtle affective cues in digital environments can influence economic decision-making in measurable ways.

Keywords: Emoji; risk preferences; online experiment

INTRODUCTION

Digital communication increasingly relies on visual and affective cues that may shape how individuals interpret information and make decisions. This is especially relevant in online environments, where people are frequently exposed to subtle signals that can influence judgement despite carrying little explicit informational content. Studying whether seemingly small digital signals, such as emojis, can affect economic behaviour in measurable ways is therefore increasingly important. Recent experimental evidence also suggests that simple smiling cues can embody information that influences behaviour in economic interactions, highlighting that even minimal nonverbal signals may matter in decision-making contexts (Drouvelis & Grosskopf, 2021). This question is especially important when it comes to risk preferences, which play an important role in many everyday and real-life decisions. People often have to make choices under uncertainty, such as whether to invest money, buy insurance, change careers or adopt new technologies. Understanding the factors that shape people's risk preferences is crucial to behavioural economics because these preferences affect how people evaluate uncertain outcomes. If subtle affective cues can alter risk attitudes, this would have broader implications for decision-making in increasingly digital settings.

One such cue is the emoji, which has emerged as a key component of digital communication. Emojis serve as paralinguistic cues that transmit emotional meaning beyond written text. Aldunate and Gonzalez-Ibanez (2017) argue that emojis enhance text-based communication by conveying tone and emotion that may be absent in verbal content alone. This can be understood through the concept of textual paralanguage (TPL), defined as written representations of nonverbal cues that implement or substitute for language in computer-mediated communication (Luangrath, Peck & Barger, 2017). Much like facial expressions, gestures and vocal tone in face-to-face interaction, emojis provide contextual information that shapes interpretation and response. Their growing use in daily communication, including their symbolic recognition as Oxford Dictionaries' "Word of the Year" in 2015 (Dictionary.com, 2015), reflects their communicative significance. Among the different categories of emojis, positive-valence emojis are especially common and are typically linked to happiness, friendliness, warmth and approval.

The potential impact of emojis on decision-making aligns with extensive research on nonverbal communication in economics. Drouvelis and Grosskopf (2021) observe that although verbal and face-to–face communication have garnered substantial attention, there is considerably less understanding of simpler nonverbal cues, despite their commonality in natural settings. Their research underscores that smiling cues, such as smiling-face emoji, can serve as conduits of social information in economic exchanges. In digital contexts, emojis may function as effective substitutes for facial expressions by transmitting emotional meaning even without physical presence.

This notion is corroborated by established theories of emotion and social judgement. The Emotions as Social Information (EASI) framework posits that emotional expressions can affect recipients via two mechanisms: social inference and affective responses (Van Kleef, 2009). People may see emotional expressions as signals about a sender's intentions, while also experiencing affective contagion, whereby their emotions change in response to what they see. Erle et al. (2022) demonstrate that emojis can trigger emotional contagion, while Ely et al. (2025) utilise electroencephalography (EEG) to reveal that face-like emojis elicit neural responses akin to those generated by actual human faces. These findings indicate that emojis are not merely ornamental elements of online messages, but significant affective stimuli.

If emojis can evoke emotional responses, these emotions may subsequently affect judgement in risky situations. The Affect Infusion Model (AIM) posits that affect is more likely to influence judgement when individuals engage in heuristic or substantive processing rather than merely retrieving a pre-existing judgement (Forgas, 1995). Prior research indicates that positive affect may cause individuals to interpret ambiguous outcomes with greater optimism and prioritise favourable information (Forgas, 1982, 1989, 1994; Nygren et al., 1996, Yuen & Lee, 2003). However, mood maintenance theory posits that individuals in a positive emotional state may exhibit increased caution to sustain that state and avert consequences that could jeopardise it (Isen & Patrick, 1983). These conflicting viewpoints suggest that the influence of positive affect on risk-taking remains theoretically uncertain.

Although emojis are commonly used in digital contexts, there is a paucity of research investigating their impact on economic decision-making, especially in relation to experimentally induced risk preferences. Current research predominantly examines message interpretation, interpersonal perception, or marketing outcomes, whereas the function of emojis in incentivised behavioural experiments is inadequately investigated. This gap is particularly significant as an increasing number of behavioural experiments and economic decisions are executed online, where emojis and other digital cues often accompany information and may subtly influence responses.

The study aims to examine how exposure to neutral versus positive emojis influences individuals' risk preferences in an online experiment. Drawing on the Affect Infusion Model, one prediction is that exposure to positive emojis will increase risk-taking behaviour relative to neutral emojis, as positive affect promotes more optimistic evaluations of uncertain outcomes. In contrast, mood maintenance theory suggests the opposite prediction: exposure to positive emojis may decrease risk-taking behaviour, as individuals in a positive emotional state may avoid risky choices to preserve their mood. The present experiment serves as a test of these competing hypotheses.

METHODOLOGY

This study used an online between-subjects experiment designed in Qualtrics, and administered to participants through Prolific. The study was approved by Nanyang Technological University (SSS/ECON/2025/S1/013_E_Nov). Participants first provided informed consent, read instructions explaining the lottery task and token-based bonus payment system, and completed comprehension questions before proceeding.

Risk preferences were elicited using a Multiple Price List (MPL) method adapted from Holt and Laury (2002). Participants completed three sets of 10 lottery-choice rounds, choosing repeatedly between a relatively safer option and riskier option. For example, participants had to choose between Option A, which offered a lottery with a 50% chance of receiving 100 tokens and 50% chance of receiving 0 tokens, and Option B, which offered a guaranteed payoff of 50 tokens. Across rounds, the payoff of the safer option varied systematically, allowing the switching point between the safer and riskier options to serve as a measure of risk preference. The fixed exchange rate for tokens was 100 tokens=£1.00. After completion of the entire survey, participants received a guaranteed £1.25 participation fee. One lottery decision was then randomly selected from the 30 decision questions to determine each participant's bonus payment.

The emotional valence of the emoji displayed during the primary lottery task served as the primary treatment variable. Participants were randomly assigned to either a control condition, where a neutral emoji (😶) was displayed, or a treatment condition, where a positive emoji (😊) was displayed. Other than that, every condition's instructions, wording, task structure and survey content were identical. Each of the 30 lottery decisions was shown on a separate page with task instructions and the designated emoji at the end to maintain the visual prime salient. This resulted in a total of 30 exposures. The emoji only appeared in the main lottery task and nowhere else in the survey. A validated standardised emoji dataset was used to choose the neutral and positive emojis, with the neutral emoji serving as a baseline close to the neutral midpoint and the positive emoji representing strong positive sentiment (Kutsuzawa et al., 2024).

The dependent variable was the number of certain outcomes selected, which indicated the participants' revealed risk preference based on their MPL selections. A higher value of this measure indicated greater risk aversion and a stronger preference for the safer option. In addition, a number of control variables were also collected, such as employment status, gender, education level and age (calculated from birth year). The Positive and Negative Affect Schedule (PANAS) was used to measure the participants' affective states (Watson et al., 1988). Other perception variables included their level of relaxation during the task and their likelihood of winning the lottery.

To assess demand effects, participants were asked at the end of the survey to guess the purpose of the experiment. This question was placed before the manipulation check to avoid prompting them to focus on specifically the emoji. The manipulation check then asked which emoji they had noticed during the task, allowing the study to verify whether participants had attended to the visual prime. Together, these post-experimental measures assisted in evaluating treatment awareness as well as the potential that participants' behaviour was impacted by their comprehension of the study's goal.

RESULTS

The complete dataset consists of 399 participants, of whom approximately 56% were female. Risk preferences were elicited using three rounds of MPL, and behaviour is summarised using risk_avg, defined as the average number of safe choices across the three rounds (higher values indicate greater risk aversion). We estimate the treatment effect using Ordinary Least Squares (OLS), regressing risk_avg on the treatment variable (1 = positive emoji condition), with robust standard errors.

Participants exhibiting multiple switch points in any MPL round were excluded in (2). This restriction leaves 237 valid observations. Additionally, a stricter restriction was imposed in (3), whereby participants who incorrectly identified the emoji in the manipulation check were excluded, leaving 173 valid observations. Further, the demand-effects check yielded no additional exclusions.

TABLE 1. MAIN REGRESSION RESULTS

	(1)	*(2)*	*(3)*
Dependent Variable: *risk_avg*			
treatment	0.636*	0.904**	0.882**
	(0.353)	(0.436)	(0.445)
female	0.275	0.179	0.263
	(0.207)	(0.277)	(0.329)

age	0.006	0.004	-0.016
	(0.010)	(0.013)	(0.015)
constant	2.943***	2.680***	3.492***
	(0.546)	(0.717)	(0.756)
No. of obs	399	237	173

Note: (1) represents the full sample, (2) excludes participants with multiple switch points in any MPL round, (3) further excludes those who failed the manipulation check. *treatment* = 1 for the positive emoji condition, and *treatment* = 0 for neutral emoji condition. *female* is a dummy variable where *female* = 1 when the participant is female and *female* = 0 otherwise. *age* represents the current age of the participant. Additional controls include: *education* and *employment* categorical dummy variables. Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Across all specifications, treatment coefficient is positive, indicating that participants in the positive emoji (treatment) condition select more safe options on average than those in the neutral emoji (control) condition. Restricting the sample in (2) yields a higher treatment coefficient than (1), with the estimated effect being significant at a 5% level. The treatment effect remains statistically significant and of similar magnitude when additionally excluding participants who failed the manipulation check. Overall, the results suggest that exposure to positive emojis is associated with greater risk aversion, and this pattern becomes more pronounced when applying stricter data quality restrictions.

We evaluate our three proposed channels — PANAS, perceived probability of winning the lottery task, and self-reported relaxation — using a two-step mediation analysis. First, we test whether treatment predicts the channel. Subsequently, we test whether the channel predicts risk_avg. All regressions in the mediation analysis utilise the sample that excludes participants with multiple switching points and include the same set of demographic controls (female, age, and categorical dummies for education and employment).

TABLE 2. MEDIATION ANALYSIS

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Dependent Variable:	*net_panas*	*risk_avg*	*relaxation*	*risk_avg*	*lottery*	*risk_avg*
treatment	1.170		-0.223		0.533	
	(1.716)		(0.222)		(0.367)	

net_panas		0.010				
		(0.017)				
relaxation				0.144		
				(0.118)		
lottery						0.075
						(0.089)
constant	15.148***	3.443***	5.672***	2.832***	3.397***	3.320***
	(2.962)	(0.601)	(0.384)	(0.773)	(0.531)	(0.671)
No. of obs	237	237	237	237	237	237

Note: Regressions (1), (3) and (5) report the first-step of the mediation analysis, regressing each channel variable (*net_panas*, *relaxation*, and *lottery*, respectively) on *treatment*. Regressions (2), (4) and (6) report the second-step, regressing *risk_avg* on the corresponding channel variables. All specifications use the sample that excludes participants with multiple switching points, and include the same demographic controls as the main specification (*female*, *age*, and categorical dummies for *education* and *employment*). Robust standard errors are in parentheses.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 2 reports the two-step mediation check for our three proposed channels. The net_panas score is computed as Positive Affect minus Negative Affect, where each component is the sum of its respective PANAS items. The relaxation variable is the participants' self-reported relaxation level while the lottery variable captures their perceived probability of winning the lottery task (both on a 1 to 7 scale). In the first-step regressions [Columns (1), (3), (5)], treatment does not significantly predict any of the proposed channels, indicating no detectable treatment effect on the three channels. In the second-step regressions [Columns (2), (4), (6)], the corresponding channel variables also do not significantly predict risk_avg. Taken together, we find limited evidence that the treatment effect on risk preferences is mediated by these affective or perception-based channels.

DISCUSSION AND LIMITATIONS

We observed that the participants in the positive emoji condition selected more safe choices on average compared to those in the neutral emoji condition. The treatment effect is positive across all three specifications, gaining statistical significance at the 5% level once data quality restrictions were applied. The effect remained robust in magnitude and significance when restricting the sample to participants who correctly identified the emoji in the manipulation check, suggesting that the result is not driven by inattention to the prime. The absence of demand effects further supports the validity of the findings, as no participants correctly identified the purpose of the study. Overall, the results are consistent with the prediction that positive emoji exposure decreases risk-taking, where exposure to positive emojis is associated with greater risk aversion.

Several limitations should be noted when interpreting these findings. First, the mediation analysis was designed to probe the mechanism underlying the prediction that positive emoji exposure increases risk-taking, as channels aligned with both competing predictions could not be collected given practical constraints on survey length and participant burden, which are common in online experiments. Future studies should include channels aligned with both competing predictions. Second, the manipulation consisted of a single emoji pair, and findings may be specific to those particular stimuli. Future work could vary emoji valence more systematically by utilising multiple positive stimuli, or introducing a negative emoji condition to construct a fuller picture of how affective valence shapes risk preferences. Lastly, while this study contributes to the broader emoji literature by demonstrating that subtle affective cues in digital environments can influence revealed preferences in ways that are economically meaningful, future research could also strengthen external validity and practical relevance by extending it to real-stakes financial decisions or naturalistic digital environments such as investment platforms or insurance interfaces.

Nevertheless, the observed pattern of results can be interpreted through the lens of mood maintenance theory. One possible explanation for why the AIM prediction did not hold is that the affective prime used may have been too subtle to induce a sustained positive affect which AIM requires. Additionally, mood maintenance effects may be more likely to arise in contexts where the potential for negative outcomes is salient, as individuals may avoid risk in order to preserve their positive emotional state. In contrast, AIM-consistent effects, such as more optimistic evaluation of uncertain outcomes, may be more likely to emerge in settings where outcomes are more ambiguous or less strongly framed around potential losses. The present design, where the safe option guaranteed a positive payoff and the risky option always carried a chance of receiving nothing, may therefore have been more conducive to mood-protective behaviour instead.

Despite the significant main treatment effect, the mediation analysis provides no evidence that the proposed channels mediate the relationship between emoji exposure and risk preferences. The null mediation results are nonetheless informative. Net PANAS, perceived probability, and relaxation were selected to operationalise three candidate channels — affect infusion as specified by AIM, optimistic outcome evaluation, and reduced arousal — through which positive emoji exposure was predicted to increase risk-taking. Finding no treatment effect on any of these channels rules out each as the operative mechanism. That the main effect persists without detectable changes in these measures suggests mood maintenance may instead operate through a more implicit route, one that does not surface in self-reported affect or cognitive assessments. This is consistent with Isen and Patrick (1983), who note that mood-protective behaviour can occur outside of conscious awareness.

This study demonstrates that exposure to positive emojis is associated with greater risk aversion, consistent with mood maintenance theory. These findings carry practical implications for digital platform design — financial and insurance interfaces increasingly embed affective elements, including emojis, icons, and sentiment-laden imagery, into the interfaces through which users make real-stakes decisions. If positive affective cues systematically increase caution, seemingly innocuous design choices may nudge users toward or away from risk in unintended ways. This is particularly relevant in retail investing, where incidental affective cues could lead individuals to forgo returns, while in insurance or savings contexts, the same caution could prove beneficial. Policymakers and consumer protection bodies may therefore wish to consider affective interface design as a dimension of digital nudging that warrants greater scrutiny. As emojis become increasingly ubiquitous in online environments where consequential decisions are made, understanding their downstream effects on economic behaviour remains an important avenue for future research.

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APPENDIX

TABLE A1: MAIN REGRESSION RESULTS

	(1)	*(2)*	*(3)*
Dependent Variable: *risk_avg*			
treatment	0.636*	0.904**	0.882**
	(0.353)	(0.436)	(0.445)
female	0.275	0.179	0.263
	(0.207)	(0.277)	(0.329)
age	0.006	0.004	-0.016
	(0.010)	(0.013)	(0.015)
education (ref: less than high school)			
High school diploma	0.537	0.438	0.385
	(0.397)	(0.465)	(0.520)
Associate degree	1.013***	1.117*	1.024
	(0.326)	(0.618)	(0.636)
Bachelor's degree	0.890**	0.693	0.0153
	(0.420)	(0.512)	(0.510)
Master's degree	1.248**	0.928	0.797
	(0.489)	(0.706)	(0.628)
Doctorate degree	2.552***	3.235**	0.722
	(0.873)	(1.473)	(1.128)
employment (ref: Employed/student)			

unemployed	-0.252	-0.271	-0.149
	(0.423)	(0.528)	(0.552)
out of labour force	-0.151	-0.0642	-0.138
	(0.297)	(0.380)	(0.476)
constant	2.943***	2.680***	3.492***
	(0.546)	(0.717)	(0.756)
No. of obs	399	237	173

Note: All specifications include the same demographic controls (*female*, *age*, and categorical dummies for *education* and *employment*). Robust standard errors are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

TABLE A2. MEDIATION ANALYSIS

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Dependent Variable:	*net_panas*	*risk_avg*	*relaxation*	*risk_avg*	*lottery*	*risk_avg*
treatment	1.170		-0.223		0.533	
	(1.716)		(0.222)		(0.367)	
net_panas		0.010				
		(0.017)				
relaxation				0.144		
				(0.118)		
lottery						0.075
						(0.089)
female	-0.803	0.195	-0.491***	0.258	-0.156	0.198
	(1.176)	(0.279)	(0.164)	(0.295)	(0.236)	(0.279)
age	0.079	0.002	0.004	0.002	-0.012	0.003
	(0.051)	(0.013)	(0.006)	(0.013)	(0.010)	(0.013)
education (ref: less than high school)						

High school diploma	2.340	-0.154	-0.012	-0.156	0.918**	-0.180
	(1.920)	(0.348)	(0.285)	(0.350)	(0.373)	(0.347)
Associate degree	6.895***	0.884	-0.003	0.948	1.609***	0.841
	(2.389)	(0.647)	(0.327)	(0.611)	(0.431)	(0.634)
Bachelor's degree	4.755**	-0.101	0.130	-0.107	1.184***	-0.117
	(2.077)	(0.337)	(0.264)	(0.342)	(0.425)	(0.337)
Master's degree	3.370	0.106	-0.486	0.172	0.842	0.102
	(2.688)	(0.553)	(0.339)	(0.553)	(0.586)	(0.532)
Doctorate degree	4.403	2.312*	-1.934***	2.593*	2.037*	2.234
	(3.624)	(1.393)	(0.547)	(1.357)	(1.215)	(1.438)
employment (ref: Employed/ student)						
unemployed	-6.438***	-0.180	-0.271	-0.207	-0.951**	-0.177
	(1.970)	(0.556)	(0.281)	(0.562)	(0.435)	(0.546)
out of labour force	-0.549	-0.129	-0.129	-0.120	-0.231	-0.115
	(1.696)	(0.380)	(0.194)	(0.378)	(0.284)	(0.379)
constant	15.148***	3.443***	5.672***	2.832***	3.397***	3.320***
	(2.962)	(0.601)	(0.384)	(0.773)	(0.531)	(0.671)
No. of obs	237	237	237	237	237	237

Note: All specifications include the same demographic controls (*female*, *age*, and categorical dummies for *education* and *employment*). Robust standard errors are in parentheses.

* p<0.10, ** p<0.05, *** p<0.01