B ELECTRONIC SUPPLEMENT

Manuscript submitted to ACM

uoquine Author	Year	Samble Size	Example 2 Study	online experiment	Field study	Survey TA	ad Interviews	Conceptual	Facebook	Twitter/X	General	Other	Social media posts	articles	Text	Images	Video	I Uther	Marming nte	Correction/debunking	E Showing indicators	g (Binary) label	Highlighting design	Usibility reduction	Removal	Complicate sharing	Specific visualization	Other	ur Active	Passive ara.	L Pre exposure	in During	At the moment of sharing	On request	Post exposure	Other	O Mis-/Disinformation	Rumors	device the second secon	Other	Browser extension/Plugin	Own platform	Other	CUILUI -
Agley et al. [2]	2021	1,000		•							•							•										•	•		-	•					•						•	1
Aird et al. [3]	2018	370	•	•							•							•		•										•		•								•			•	1
Almaliki [4]	2019	100				•					•		•															•		•						•	•						•	•
Amin et al. [6]	2021	38		٠								•						•					•			٠			•			•	•				•					•		1
Andi and Akesson [7]	2020	1,003				•					•		•						•										•			•					•						•	,
Ardevol-Abreu et al. [8]	2020	N1=31 N2=350				•	•				•		•						•					•					•			•					•						•	,
Aslett et al. [9]	2022	N1=3,862 N2=3,337 N3=968			•	•						•						•				•	•							•		•							•		•			
Autry and Duarte [11]	2021	N1=357 N2=75	•								•							•		•										•					•		•						•	
Axelsson et al. [12]	2021	N1=90 N2=119		•							•		•			•	•											•			•					•	•						•	,
Ayoub et al. [13]	2021	244		•							•				•						•									•		•					•					•		
Bachmann and Valenzuela [14]	2023	1,472		•					•				•							•	•									•		•					•						•	,
Barman and Colan [16]	2023	348		•							•		•						•	•										•		•					•						•	,
Barua et al. [17]	2019	-						٠				•			•							٠									•			•			٠					•		
Bhuiyan et al. [18]	2021	N1=430 N2=12	•		•					•			•						•				•	•						•		•							•		•			
Bhuiyan et al. [19]	2021	31	•				•					•		•							•		•							•		•							•				•	,]
Bhuiyan et al. [20]	2018	16			•					•			•						•				•	•						•		•							•		•			

Table 2. Categorization of 172 publications regarding user intervention characteristics and methodological aspects.

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Author	Year	Sample Size	Lab study	Online experiment	Field study	Survey	Interviews	Conceptual	Facebook	Twitter/X	General	Otner Social media nosts	Articles	Text	Images	Video	Other	Warning	Correction/debunking	Showing indicators	(Binary) label	Highlighting design	Visibility reduction	Removal	Complicate sharing	Specific visualization	Other	Active	Passive	Neither/unclear	Pre exposure	During	At the moment of sharing	On request	Post exposure	Other	Mis-/Disinformation	Rumors	News credibility	Other	Browser extension/Plugin	Own platform	Game Other
Author	Year	Sample Size	Ev	alua	itio	n Ty	pe		Pla	tfoi	m	F	orm	at				Int	erv	enti	on	Des	ign					Int	era	•	Tin	ning	ş				Сог	nce	pt		Imj	plen	1.
Bode and Vraga [22]	2015	N1=524 N2=500				•			•				•						•										•			•					•						•
Bode and Vraga	2018	136		•					•				,						•										•			•	_			Π	•			1	•	-	
Bozarth et al. [24]	2023	18					•					• •	•						•	•	•									•		•					•	-		1	+		•
Brashier et al. [25]	2021	2,683		•							•	•	•								•								•		•	•	_		•	Π	•				1		•
Buczel et al. [28]	2024	337		•							•		•					•										•	•		•				•	Π	•						•
Capraro and Celadin [30]	2022	N1=550 N2=558 N3=550 N4=372		•					•			•	•														•			•			•				•						•
Caramancion [31]	2022	327		•							•						•		•	•							•	•			•						•						•
Challenger et al. [32]	2022	N1=1,291 N2=2.084		•							•						•		•											•						•				•			•
Chen et al. [34]	2022	10					•		•			•	•													•				•			-	•			•	-		-		-	•
Chen and Tang [35]	2022	415		•							•						•										•	•			•						•						•
Chiang et al. [37]	2022	60		•							•		•							•										•				•					•			•	
Clayton et al. [38]	2020	2,994				•			•				•					•									•		•		•	•					•						•
Craig and Vi- jaykumar [39]	2023	231		•								•		•					•								•		•		•				•		•						•
Dai [41]	2021	350		•							•			•					٠								•		•		•				•		•	-		-	-		•
Dai et al. [40]	2022	N1=425 N2=625				•					•			•					٠											•		•				\square	•						•
Danry et al. [42]	2020	18	•									•			1		•										٠			•		٠					•			1	\neg	-	•
Denner et al. [43]	2023	211		•					•				•						•										•						•		•						•
Desai and Reimers [44]	2023	365		•						•									•										•						•		•						•
Dobber et al. [45]	2023	1,054		•								•				•		•			•							•	•		•	•								•			•
Domgaard and Park [46]	2021	250		•							•		•							•						•			•		•						•						•
Drolsbach and Pröllochs [47]	2023	7		•						•			•						•										•			•					•						•
Duncan [48]	2020	390				٠						•		•													•		•			•							٠				•
Ecker et al. [49]	2020	2,279		•							Τ	•	•						٠										•						•	I T	•						•

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Author	Year	Sample Size	Eva	alua	atio	ı Ty	pe		Pla	atfo	rm		For	mat	t			1	Inte	erve	enti	on I	Desi	ign					Int	era	.	Гin	ning	s				Co	nce	pt		Im	plen	n.
Ecker et al. [50]	2017	60	•									•		•						•										•						•					•			•
Ecker et al. [52]	2011	N1=161 N2-138	•									•		•						•										•						•					•			•
Ecker et al. [51]	2020	1718		•							•		•							•		٠								•			•					•						•
Feng et al. [55]	2023	595		•						•						•	•				٠								Î	•			٠					•						•
Figl et al. [56]	2023	256		•					٠				•						•			٠								•			•					•						•
Folkvord et al. [57]	2022	307		•					•				•						•									•	•			•						•						•
Freeze et al. [59]	2021	434		•								•		•					•											•						•		•						•
Furuta and Suzuki [60]	2021	-						•				•			•						•		•							•							•	•						•
Gao et al. [62]	2018	122		•							•		•						•									•		•			•					•		•			•	
Gesser- Edelsburg et al. [63]	2018	243	•	•					•				•							•										•						•					•			•
Grady et al. [64]	2021	418				٠					•		•						•			٠							٠	•		•	•			•		•						•
Grandhi et al. [65]	2021	376				•					•		•								•										•						•			•				•
Guess et al. [67]	2020	N1=9,190 N2=4,669 N3=6,439	•	•					•				•								•									•		•						•						•
Guo et al. [69]	2023	28					٠					•					•		•	•				•					٠	•		•	•					•						•
Hameleers [70]	2020	1,091		•							•			•					•	•	٠									•		•	•					•						•
Hameleers et al. [71]	2020	1,404		•						•			•							•										•			•					•						•
Hameleers and van der Meer [72]	2023	1,105		•		•					•				•				•		•								•			•						•						•
Hartwig et al. [74]	2024	N1=21 N2=18				•	•					•					•				•		•							•					•			•						•
Hartwig et al. [77]	2024	N1=44 N2=23				•	•			•			•								•		•							•			•					•						•
Hartwig et al. [76]	2024	20					•					•		Τ				•			•		•							•			•					•						•
Hawa et al. [78]	2021	-						•				•			•							•									•				٠			•					•	
Heuer and Glassman [80]	2022	N1=188 N2=208		•							•			•							•		•					•		•			•					•						•
Horne et al. [81]	2019	-						•			•		•															•			•		•					•						•
Huang and Wang [82]	2020	N1=235 N2=235		•					•				•	T						•										•						•		•					T	•
Irving et al. [83]	2022	129		•							•				•					•										•			•					•						•

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Author	Year	Sample Size	Lab study	Online experiment	Field study	Survey	Interviews	Conceptual	Facebook	Twitter/X	General	Other Social madia nosts	oouai moua posis	Articles	Text	Images	Video	Other Wr	warning	Correction/debunking	Showing indicators	(Binary) label	Highlighting design	Visibility reduction	Removal	Complicate sharing	Specific visualization	Other	Active	Passive	Netther/unclear	Pre exposure	During	At the moment of sharing	On request	Post exposure	Other	Mis-/Disinformation	Rumors	News credibility	Other	Browser extension/Plugin	Own platform	Game	Other
Author	Year	Sample Size	Eva	alua	tio	n Ty	pe		Pla	ntfo	rm	F	orı	nat				I	nte	rve	nti	on I	Desi	gn					Int	era.	·	Tin	ning	g				Co	nce	pt	1	Imp	lem	1.	
Jahanbakhsh and Karger [85]	2024	32		•		•					•		•									•					•			•			•					•	Τ	Τ	T	•			
Jahanbakhsh et al. [89]	2022	N1=154 N2=14			•	•					•		•									•	•				•		•				•	٠				•					•		
Jahanbakhsh et al. [87]	2021	1,668				•					•		•													•			•					•				•							•
Jahanbakhsh et al. [86]	2023	61		•						•			•									•	•					•			•		•					•							•
Jahanbakhsh et al. [88]	2022	N1=27 N2=312			•	•					•			•						•							•			•			•					•				•			
Jahng et al. [90]	2021	205		٠							•			•						•										•			٠					•							٠
Jennings and Stroud [92]	2021	N1=1,262 N2=1,586		•					•				•						•											•			•					•							•
Jeon et al. [93]	2024	N1=6 N2=94		٠	٠		•				•			•													•			•					٠						•		•		
Jia et al. [95]	2022	1,677		٠							•		•									•								•			٠					•							٠
Joshi et al. [96]	2023	-						٠			•		•								٠		•							•			٠					•							٠
Karduni et al. [97]	2019	5					•			•			•								•						•				•	•			•			•		•			•		
Kessler and Bachmann [98]	2022	700		•							•							•		•							•			•						•					•				•
Khivasara et al. [99]	2020	-						•				•			•							•							•						•			•				•			
Kim et al. [100]	2019	N1=590 N2=299				•			•				•															•		•			•					•		•					•
Kim et al. [101]	2019	-						٠				•	•														•	•			•				•						•		•		
Kim et al. [102]	2021	92	•							٠			•							•										•			•					•							٠
Kim et al. [103]	2023	N1=17 N2=57 N3=49	•				•			•			•								•		•	•		•			•	•		•			•			•				•			
Kirchner and Reuter [104]	2020	N1=1,012 N2=15 N3=1,030				•			•				•						•	•				•		•			•	•		•	•	•				•							•
Koch et al. [105]	2023	571		٠					•				•						•		٠							•	•	•			•					•		\neg	+	-	-	+	•
Komendantova et al. [106]	2021	N1=103 N2=68 N3=50					•				•		1	T				•										•		1	•						•	•	1	1	1	•	\uparrow		
Kreps and Kriner [107]	2022	2,000		•							•							•	•	•		•		•					•				•					•							•
Lee [108]	2022	171		٠					•				•							•		•								•						٠		•			T	•			٠
Lee et al. [111]	2022	-						٠				•						•			٠	•	•				•				•				٠			•		\neg	\neg		•		
Lee and Bissell [109]	2023	377		•					•				•						•	•		•							•	•		•	•					•							•

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Author	Year	Sample Size	Lab study	Online experiment	Field study	Survey	Interviews	Conceptual	Facebook	Twitter/X	General	Other	Social media posts	Articles	Text	Images	Video	Other	Warning	Correction/debunking	Showing indicators	(Binary) label	Highlighting design	Visibility reduction	Removal	Complicate sharing	Specific visualization	Other	Active	Passive	Neither/unclear	Pre exposure	During	At the moment of sharing	On request	Post exposure	Other	Mis-/Disinformation	Rumors	News credibility	Other	Browser extension/Plugin	Own platform	Game	Other
Author	Year	Sample Size	Eva	alua	tio	ı Ty	pe		Pla	tfo	rm		Foi	ma	t				Int	erv	enti	ion	Des	ign					Int	era	•	Tin	nin	g				Co	nce	pt		Imj	plen	n.	
Lee and Bissell [110]	2024	502		•					•				•							•										•			•			•		•							•
Liaw et al. [113]	2013	?		•								•		•						•			•							•			٠					•			-	•			
Lillie et al. [114]	2024	469		•							•			•						٠										•						•		•							•
Lim and Per- rault [116]	2023	36		•							•		•						•			•								•			•					•							•
Lim and Per- rault [115]	2023	200		•							•		•						٠			•								•			•					•							•
Liu et al. [117]	2023	859		٠						•			•							٠										•						•		•							•
Lo et al. [118]	2021	89		٠							•			•						٠											•		٠					•					•		
Lu et al. [119]	2022	N1=538 N2=1,098		•							•			•								•						•		•			•			•		•							•
Martel et al. [120]	2021	2,228		•					•	•			•							•										•						•		•							•
Martino et al. [121]	2020	-						•				•			•						•		•								•				•						•		•		
Mena [122]	2020	501		٠					٠				•						٠											•			٠					•							٠
Moon et al. [125]	2022	354		•					•				•							•										•			•					•							•
Moravec et al. [126]	2020	398		•					•				•						•			•						•		•		•	•					•							•
Nekmat [127]	2020	929		٠								٠		•					٠											•			٠					•							•
Ozturk et al. [129]	2015	259				•				•			•						•	•										•			•						•						•
Papakyriakopoul and Goodman [131]	os 2022	-						•		•			•						•			•								•			•					•							•
Pareek and Goncalves [132]	2024	96		•							•			•								•								•					•			•							•
Park et al. [133]	2021	11,145				٠						٠			•				٠								•			•			٠						٠						•
Pasquetto et al. [134]	2022	N1=2,805 N2=25		•			•					•						•		•		•						•		•						•		•							•
Pennycook et al. [135]	2020	N1=5 271 N2=1,568		•					•				•						•			•								•			•					•							•
Pennycook et al. [137]	2020	N1=853 N2=856				•					•		•															•	•			•						•							•
Pennycook et al. [136]	2021	N>5,000			•	•				•			•															•		•		•				•		•							•
Pillai and Fazio [139]	2023	499		•														•										•		•						•		•							•

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Author	Year	Sample Size	Eva	alua	tior	ı Ty	pe		Pla	tfoi	m	F	orn	at				Int	erv	enti	on	Desi	ign					Int	era	.	Гim	ing	Ş				Co	nce	pt		Imŗ	plem	a.	
Pluviano et al. [140]	2017	120	•								•			•					•							•			•			•				1	•			•				•
Porter and Wood [142]	2022	N1=5,000 N2=2,000		•					•				•					•	•		٠		•					•				•					•							•
Porter et al. [141]	2022	5,075		•							•		•						•										•			•					•							•
Pourghomi et al. [144]	2017	-						•	•				•		•											•			•					•			•							•
Pretus et al. [145]	2024	N1=1,709 N2=804		•						•			•					•		•							•		•			•					•							•
Prike et al. [146]	2024	415		•							•		•							•	٠					•			•			•				+	•	-	-	-	-	-	+	٠
Qian et al. [148]	2023	905		•							•				•											٠		٠	•		•					\neg	•		-			_		٠
Rich and Zaragoza [150]	2020	N1=134 N2=134 N2=102		•								•	•	•					•										•						•	T	•			Τ				•
Ruffin et al. [153]	2022	N1=113 N2=543				•					•				•	T				•		•							•		1	•				+	1		1	•	1	+	+	•
Scharrer et al. [161]	2022	41		•							•			•				•			•								•		•	•				T	•			Τ				•
Safieddine et al. [154]	2016	-						٠				•		•	•											•			•					•			•				•	•		
Sakhnini and Chattopadhyay [155]	2022	11					•				•						•		•	•	•									•				•			•					•		
Saltz et al. [157]	2021	N1=15 N2=23					•				•		•		•	•		•			٠		•	•			٠	•	•							•	•							٠
Sangalang et al. [159]	2019	N1=385 N2=586		•								•		•					•										•						•		•							•
Schaewitz and Kramer [160]	2020	221		•								•	•	•					•										•						•		•							•
Schmid et al. [163]	2022	N1=9 N2=7		•			•			•			•							•	•					•				•				•			•					•		
Schmid and Betsch [162]	2022	N1=2,444 N2=817		•							•			•					•									•			•				•		•							•
Seo et al. [165]	2019	N1=522 N2=624		•							•		•					•											•			•					•							•
Sharevski and Gover [167]	2021	304				•				•							•										•	•	•			•					•							•
Sharevski and Zeidieh [168]	2023	29					•				•					•		•			٠								•			•					•							•
Sharevski et al. [166]	2022	337		•						•			•					•											•			•					•					\square		•
Sheikh Ali et al. [169]	2023	-						•		•				•					•	•	•	•							•					•			•							•

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Author	Year	Sample Size	Lab study	Online experiment	Field study	Survey	Interviews	Conceptual	Facebook	Twitter/X	General Other	Social media posts	Articles	Text	Images	Video	Other	Warning	Correction/debunking	Showing indicators	(Binary) label	Highlighting design	Visibility reduction	Removal	Complicate sharing	Specific visualization	Other	Active	Passive	Neither/unclear Pre exposure	During	At the moment of sharing	On regulact	Dest amount	rust expusure Othor	Other Min_/Disinformation		NTAUTO ANA Athility	News credibility	Uther · · · · · · ·	Browser extension/Flugin	Own platform	Game	Other
Author	Year	Sample Size	Ev	alua	ntior	ı Ty	pe		Pla	ntfo	rm	Fo	rma	at				Int	erv	enti	on	Des	ign					Int	era	. Т	imi	ng				C	Con	cep	ot	I	mp	lem	•	
Sherman et al. [170]	2021	N1=24 N2=19 N3=1,456		•			•				•					•		•		•	•	•	•			•			•			•				•	•							•
Smith and Seitz [174]	2019	744		•					•								•		•										•		,	•				-	•			•		T	-	•
Song et al. [175]	2022	610		•					•			•							•										•			•				-	•							•
Sotirakou et al. [176]	2022	-						•			•						•		•		•						•			•				•		•	•					•		
Sullivan [177]	2019	N1=625 N2=600		•					•			•							•										•			•				1	•				Т			•
Tanaka and Hi- rayama [178]	2019	164		•						•		•							•										•						•	+	-	•			+	+	,	•
Tanaka et al.	2013	87		•						•		•							•										•		•				•	+	-	•			+	+	-	•
Tao et al. [180]	2023	836		•							•	•							•										•						•	+,	•	-		+	+		-	•
Thornhill et al. [182]	2019	20				•				•				•					•		•	•							•			•					•					•		_
Tseng et al. [183]	2022	210		•							•			•	•	•			•										•						•		•							•
Tsipursky et al. [184]	2018	21			•				•			•															•	•		-	•					1	•		T		T	T	,	•
Tulin et al. [185]	2024	752		•							•		•						•		•								•			•				+,	•			-	+	-	-	•
Tully et al. [186]	2020	610		•						•		•							•										•			•				1	•				+			•
Tully et al. [187]	2020	N1=702 N2=787		•						•		•															•		•	-	•					•	•						7	•
van der Meer and Jin [189]	2020	700		•							•		•						•										•						•		•							•
van der Meer et al. [188]	2023	1,305		•							•		•					•	•								•		•						•	•	•						·	•
Velasco et al. [190]	2023	285				•					•			•							•									•				•		•	•				•			
Velez et al. [191]	2023	2,869		•							•	•							•										•						•		•							•
von der Weth et al. [192]	2020	-						•		•		•						•		•					•		•	•				•	•			•	•				•			
Vraga et al. [196]	2021	916		•						•		•							•								•		•			•				•	•						,	•
Vraga and Bode [193]	2018	1,384		•						•		•							•										•		,	•					•						,	•
Vraga and Bode [197]	2017	271		•					•	•		•							•										•			•					•	Τ			T	T	1	•
Vraga et al.	2022	N1=1,207 N2=603		•						•		•							•								•		•		,	•					•				1	1	,	•

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Author	Year	Sample Size	Lab study	Online experiment	Field study	Survey	Interviews	Conceptual	Facebook	Twitter/X	General	Ouner Social media nosts		Articles	Images	Video	Other	Warning	Correction/debunking	Showing indicators	(Binary) label	Highlighting design	Visibility reduction	Removal	Complicate sharing	Specific visualization	Other	Active	Passive	Neither/unclear	Pre exposure	During	At the moment of sharing	On request	Post exposure	Other	Mis-/Disinformation	Rumors	News credibility	Other	Browser extension/Plugin	Own platform	Game Athan	Other
Author	Year	Size	Eva	alua	tior	ı Ty	pe		Pla	tfo	m	F	orn	nat				In	terv	rent	ion	Des	ign					Int	tera	•	Tin	ning	g				Co	nce	pt		Imj	plem	ι.	
Vraga et al. [194]	2021	1348		•					•							•			•								•		•		•	•					•						,	•
Vraga et al. [199]	2019	406		•					•				•						•										•						•		•							•
Vraga et al. [195]	2020	1,005		•								•	•						•								•	•	•		•				•		•						-	•
Wahlheim et al. [200]	2020	96	•								•						•		•								•		•						•		•						-	•
Waltenberger et al. [201]	2023	9			•		•					•	•							•	•								•			•					•				•			
Wang and Huang [204]	2021	271		•								•	•						•										•						•		•							•
Wang [202]	2022	N1=601 N2=1.060		•		٠			•			•	•	•				•	•										•			•					•							•
Wang et al. [203]	2022	1	•								•		•													•				•				•				•				•		_
Westbrook et al. [207]	2023	N1=125 N2=138 N3=251		•							•			•					•										•						•		•	Τ					•	•
Wijnker et al. [208]	2022	441		•							•						•	•	•	•		•							•			•					•	Τ					-	•
Wood et al. [210]	2023	2,257		•							•			•					•										•		•				•		•							•
Yong et al. [213]	2023	-						٠			•			•	•					•		•							•			•					•							•
Zade et al. [214]	2023	21					•			•			•							•						•			•			٠					•						'	•
Zhang et al. [216]	2022	-						•				•	•					•	•		•					•				•		•					•							•
Zhao [217]	2019	252		•					•	•		•	•						•											•						•	•							•
Zheng and Ma [218]	2022	222		•							•						•					•				•				•		•					•						•	•

Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive
Agley et al. [2]	Exposure to infographics with scientific information slightly increases		Exposure to infographics with scientific informa-
	trust in science compared to exposure to control infographic.		tion does not have direct or indirect effects on
Aird et al. [3]	Exposure to fact-checks corrects beliefs and affects voters' support		COVID-19 preventive behaviors.
1 in a ct an [5]	when corrections outnumber affirmations compared to other correction		
	ratios and for both sides of the political spectrum ($\eta^2 = 0.13$ (fact checks);		
	$\eta^2 = 0.01$ (myth:fact ratio).		
Almaliki [4]		Users perceive interventions with gami-	
		fication elements useful but preferences	
Amin et al. [6]	Interventions with Visual Selective Attention System can increase at-	for elements vary.	
Annii et al. [0]	tentive behavior of COVID-19 misinformation sharing compared to		
	pre-intervention (D-Scores similar to Cohen's d: Highest number of		
	participants in category 'Neutral/ No Preference' (D-score=-0.15 to D-		
	score=0.15)		
Andi and	Social norm-based nudge decreases misinformation sharing behavior		
Akesson [7]	compared to non-application.		Warning labels to access avadibility are not regarded
et al. [8]			as central assessment measures by users
Aslett et al. 9			Providing dynamic, in-feed source reliability labels
			do not significantly improve news diet quality or
			reduce misperceptions (<0.08 change in SD of the
			pre-treatment measure).
Autry and			Negated corrections and replacements lead to in-
Duarte [11]			previous exposure to the target concept, relative to
			cases with exposure and cases with no treatment
			$(\eta^2=0.22 \text{ (main effect of exposure)}; \eta^2=0.23 \text{ (main effect of exposure)}$
			effect of correction); $\eta^2 = 0.18$ (interaction between
			exposure and correction)).
Axelsson et al.	Observational learning and feedback as intervention tools increase user		• · · · ·
[12]	performance of credibility assessment compared to the non-treatment		
Amerika et al. [12]	control group ($\eta^2 = 0.043$)		
Ayoub et al. [15]	NI P misinformation detection model and SHAP combined with source		
	and evidence information increases user trust in misinformation detec-		
	tion compared to presenting output text only.		
Bachmann and Valenzuela [14]	Fact-checks are similarly effective at reducing people's mispercep-		Compared to control groups without intervention,
valenzuela [14]	(d=0.51 (Study 1) and d=0.28 (Study 2))		and perceive the media as more biased especially
	(d=0.51 (Study 1) and d=0.58 (Study 2))		after reading corrections debunking pro-attitudinal
			misinformation
Barman and	Warning flags with and without explanation text from fact-checking		
Colan [16]	websites reduce perceived accuracy of misinformation and intent to		
	share. Explanatory texts could enhance the trustworthiness of the inter-		
Bhuivan et al.	Credibility nudges as browser extension improve user's skills to distin-		
[18]	guish news tweets' credibility compared to control group (d=0.296)		
Bhuiyan et al.		Transparency cues (source and message	
[19]		credibility) on news websites increase	
		consumer trust.	

Table 3. Overview of effects and perceptions of reviewed misinformation interventions (conceptual studies without evaluation were excluded).

	Continued fro	om previous page	
Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive
Bhuiyan et al. [20]	Attention and reflection nudges enhance users' credibility assessment compared to control group	Attention and reflection nudges enhance users' credibility assessment (reread and rethink news; use external sources; ac- tively participate in assessment) com- pared to control group.	
Bode and Vraga	Exposure to corrective information decreases user misperceptions com-		
[22]	pared to pre-treatment and to the control group ($\eta^2 = 0.052$)		
[23]	interventions with algorithmic of social corrections are equally effective in health misinformation corrections compared to control conditions without intervention for high and low conspiracy belief individuals (η^2 =0.046 (interventions overall); η^2 =0.016 (comparison between algo- rithmic and social correction))		
Bozarth et al. [24]		Almost half of participants (moderators on Reddit) preferred cues over labels from expert fact-checkers as they can help dis- cern user intent. A quarter distrusts pro- fessional fact-checkers.	
Brashier et al.	Debunking measures have a stronger long-term impact on users' fact-		
Buczel et al. [28]	checking memory than prebunking, labeling, or no measures. Warning before misinformation reduces reliance on it in short-term in comparison to no warning. Warning after misinformation had no effect $(\eta^2=0.05 \text{ (forwarning vs. retraction only)})$		Reliance on misinformation increased for over 7 days although the memory of retraction continued.
Capraro and Celadin [30]	Accuracy endorsement prompt nudge reduces fake news sharing but also increases sharing of real news compared to simple fake alert and no-nudge (f=0.129 (two nudges); f=0.125 (two nudges, different UI); f=0.129 (comparison between endorsing accuracy condition and accu- racy salience condition))		
Caramancion [31]			Preventive infographics have trivial to no effect on social media users
Chiang et al.	AI news source credibility system positively affects users' information		
[37]	assessment and attitude towards media literacy learning.		
Challenger et al.	Myth-busting formats, question-answer formats and fact-myth formats		
[32]	haseline in reducing COVID-19 misinformation agreement ratings		
Chen and Tang [35]	Intervention with narrative fear appeal messages are effective in pro- moting health experts to correct online health misinformation for the public.		
Chen et al. [34]	Correct assessment of misinformation overall improved by VisualBub- ble. Participants became more willing to make assessments and more critical (effect sizes: Topic Filter: large (d=0.98 and 0.98); Opinion Filter: negligible (d=0.00) and medium (d=0.79); Source Filter: large (d=1.11 and 1.01))		Showed tendency to become over-skeptical
Clayton et al. [38]	Intervention with a general warning about misleading articles reduce the perceived accuracy of false headlines relative to a no-warning condition and 'rated false' tag is more effective than 'disputed' tag.(d=0.08 (general warning before seeing headlines); d=0.26 ('disputed' tag); d=0.38 ('rated false' tag))		
Craig and Vijaykumar [39]	Corrective intographic improved rating of misinformation as untruthful and reduced reported willingness to share it. Debunking may be short- lived if followed by misinformation. Effect can be maintained in presence of further corrective information (e_{g} , $p_{\pi}^2 = 0.50$, 0.109 and 0.079)		
Dai [41]	Timing of misinformation (e.g., η =0.19, 0.107 and 0079) and addition of coherence message (debiasing/no addition) impacts effectiveness (η^2 =0.087 (post exposure); η^2 =0.047 (debiasing message); η^2 =0.163 (time lapse))		

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Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive
Dai et al. [40]		Most participants indicate that counter- factual explanations can accurately ex- plain why a piece of news is fake and results suggest that the approach gener- ates the most helpful explanations com- pared to state-of-the-art methods (human evaluation based on survey with young, well advected participanto)	
Danry et al. [42]		Wearable AI system with explainable feedback enhances rationality in evalu- ating information in comparison to non- explainable AI and control group	
Denner et al. [43]	A single correction and repeated corrections significantly increased organizational trust compared with no correction		Small negative effect of perceived persuasive intent on organizational trust after repeated corrections.
Reimers [44]			son the misinformation was presented were more effective than a correction not accompanied by ex- planation
Dobber et al. [45]	Red and orange traffic light labels placed concurrently with in contrast to prior to the start of a political advertisement significantly affect credibility perception. Direct-to-consumer labels can be effective but it depends on timing and position.		
Domgaard and Park [46]	Interventions with info graphs increase user ability to identify vaccine- related misinformation compared to text-only intervention and no in- tervention		
Drolsbach and Pröllochs [47]	Community fact-checked misinformation is less viral and receives fewer retweets than non-misleading posts.		
Duncan [48]	Credibility labels are effective on news validation when ideological perspective of the user match the ideology of the news brand but also in cases where they do not match		
Ecker et al. [49]	Corrections are generally effective at influencing inferential reasoning but participations are part more affective than non-neurotice		
Ecker et al. [50]	Corrections are more effective when they explicitly repeat the myth compared to corrections that do not repeat the misinformation (η^2 =0.04 (memory): $n^2 = 0.72$ (information reasoning))		
Ecker et al. [52]	Strong corrections and cognitive load interventions, measured in dif- ferent degrees of interventions or misinformation strength, can reduce (but never fully) the continued influence effect of strong misinformation, but even strong interventions are less effective on weak misinforma- tion. (η^2 =0.05 (strength of misinformation); η^2 =0.41 (strength of correc- tion); η^2 =0.04 (strength of cognitive load on misinformation); η^2 =0.07 (strength of cognitive load on correction);)		
Ecker et al. [51]	Misinformation corrections do not lead to familiarity backfire effects but instead lead to corrective effect in both, audiences unfamiliar to a misinformation and audiences familiar to the topic (i.a., η^2 =0.024 (false claim inference across all conditions: no-exposure/fact-check with and without cognitive load); η^2 =0.004 (fact check condition without cognitive load))		
Feng et al. [55]	Provenance has effect on credibility perception. Helped correct truth judgments towards deceptive media (qualitatively measured)		Over-corrected in some cases and shifted away from truth in some non-deceptive media
Figl et al. [56]	All evaluated flags lead to reduced perceived credibility. The semantic priming effect of different warning symbols (e.g., stop symbol associated with stopping behavior) makes a difference. Stronger warnings may be required on smartphones than on PCs.		

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Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive
Folkvord et al. [57]	Interventions with source information positively affect the critical news evaluation compared to a control group with no intervention (e.g., η^2 =0.05 for vaccination misinformation)		Inclusion of a protective warning message does not significantly affect critical evaluation (e.g., $\eta^2 < 0.001$ for vaccination and health insurance misinformation).
Freeze et al. [59]	General misinformation warnings which also contain invalid instances, in contrast to valid-only instances and control with no intervention, lead to a discarding of authentic information and to increased memory uncertainty.		
Gao et al. [62]			Stance labels on political ideologies intensify read- ers' selective exposure (tendency to look for agree- able opinions), and lower the perception of extreme- ness and criticality of misinformation. Credibility labels only have a limited effect on reducing selec- tive exposure and misinformation identification.
Gesser- Edelsburg et al. [63]	Corrections of misinformation from health organizations are more ef- fective for pro-vaccination as well as for vaccination-hesitant individu- als when communication addresses full, transparent information and emotional aspects compared to 'common' one-dimensional, partial re- sponses.	Additional qualitative analysis reinforces quantitative findings.	
Grady et al. [64]	Misinformation warnings for political news are effective in short-term to correct beliefs and eliminate partisan bias but in long-term corrected beliefs weaken and biases return.		
Grandhi et al. [65]		Users perceive trustworthiness indicators as useful for reducing uncertainty and for providing guidance on content interac- tion.	
Guess et al. [67]	Digital media literacy interventions increase user ability to discern between correct information and misinformation compared to control group without intervention (d=0.2 (US-based study); d=0.11 (India-based study))		
Guo et al. [69]	Specific contextual warnings for video-sharing platforms can alert users to be vigilant and are influenced by explicitness and risk level. In terms of accuracy judgment the interstitial warning and specific contextual warning were both considered effective.		
Hameleers [70]	A combination of media literacy- and fact-checking interventions are most effective in lowering perceived accuracy of political misinfor- mation, compared to each intervention separately and control group without intervention.		
Hameleers and van der Meer [72]	General rather than issue-specific warnings about misinformation are more effective for participants with higher level of trust in the media.		The prebunking exposure to different warning in- terventions did not influence the truth rating of factually accurate information or misinformation. Observed negative spillover effects of prebunking warnings on truth rating of accurate information.
Hameleers et al. [71]	Multimodality (text-plus-visual) impacts credibility of disinformation but also of fact-checking interventions compared to disinformation and intervention with text-only and compared to control without interven- tion.		Source type (ordinary citizen, news agency) does not influence credibility level
Hartwig et al. [74]	In several instances, participants changed or consolidated their assess- ment of the information presented with the help of the indicators.	Participants found the indicators useful for practice and as a reminder to be more able to identify disinformation on their own in the future, without app support.	Adolescents tended to blindly in the intervention.
Hartwig et al. [77]	when topical, formal, and rhetorical indicators are presented with tweets, they improve users' perception and evaluation.	Approach is perceived as useful overall within the context of COVID-19 and the Russian war against Ukraine.	

Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive
Hartwig et al. [76]		When assessing the comprehensibility and perceived usefulness of features to assess a voice message's credibility, it re- ceived a mostly positive feedback espe- cially on features that refer to the content itself.	
Heuer and Glassman [80]	Checklist with source labels is significantly better in influencing partici- pants' performance on correct article ratings for the better.	Checklist that provides source labels was considered most helpful. The interactive checklist is perceived as more helpful than the unitan checklist	
Horne et al. [81]	Soft information nudging/trust nudging has potential benefit of moving even extreme or conspiracy news consumers towards higher quality information (based on simulations)	than the written checklist.	
Huang and Wang [82]	Misinformation belief is impacted by the message format (narrative/non- narrative) and correction mechanism (social/algorithmic correction) (η^2 =0.03 and 0.04 (message format);)		
Irving et al. [83]	Correction reduces number of references to misinformation (medium- to-large effect size) and was remembered and recalled (δ =0.64, 95% BCI [0.28, 0.99] (medium-to-large))		
Jahanbakhsh and Karger [85]		It helped them think about the news in a more analytical way or gauge their trust in a source. They liked being interactive with the news content and the ability to call out content they found biased or mis- leading.	Assessing took extra time and effort. Sometimes they found it hard to assess a piece of content. They want to think for themselves, unassisted by anyone.
Jahanbakhsh et al. [89]	Lightweight nudging interventions (checkboxes, checklists, free-text rationales) which provide accuracy assessment and rationale reduce misinformation sharing (but also sharing overall).		
Jahanbakhsh et al. [87]	Users perceive incorporation of three new user affordances into social media as useful tools to independent, user-friendly misinformation combat.	Qualitative examples reinforce quantita- tive findings.	
Jahanbakhsh et al. [86]	Personalized AI impacts users' judgment and grows larger over time, but is reduced when users provide reasoning for their assessment (e.g., $\exp(\beta)=1.60$ for condition whether AI's prediction had a statistically significant effect on user agreeing with AI)		
Jahanbakhsh et al. [88]	Users perceived value in browser extension that allows to change head- lines and used it to make various changes. In follow-up study: substantial number of alternative headlines were preferred especially if bias was removed or deceptions were corrected.		
Jahng et al. [90]	Discounting cues ('fake news' labels) in online comments negatively impact users' ability of veracity evaluation and increase need to au- thenticate information compared to control group without exposure to discounting cues. (i.a., η^2 =0.041 (evaluation ability); η^2 =0.057 (need to authenticate)))		
Jennings and Stroud [92]	Partisan affiliations impact likeliness to belief in misinformation, particularly about opposing parties (i.a., η^2 =0.13 (user partisanship (P) and party-affiliation of misinformation target(M)); η^2 =0.01 (P, M and fact-check condition (F))		Overall, independent from partisan affiliation, fact check interventions do not improve information evaluation compared to cases without intervention.
Jeon et al. [93]	Both the quantitative and qualitative results confirmed that HearHere has an impact on mitigating political polarization and broadening one's perspectives on news consumption.		
Jia et al. [95]	Interventions with misinformation labels (algorithm, community, third- party fact-checker, and no label) reduce credibility of misinformation for liberal users independent of post-ideology while only algorithm labels are effective in reducing ideology-consistent misinformation for conser- vative users (and all label types for opposing-ideology misinformation).		

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Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive	
Karduni et al. [97]		Visual analytic systems are a helpful tool to support the investigation of misin- formation on social media and to en- hance traditional (media literacy educa- tion) strategies.		
Karduni et al. [97]	Corrections of health-related misinformation with additional use of images is more effective in correcting myth belief than without images (η^2 =0.117)		Image type (machine-technical image, expert image, diagram) does not influence persuasive effect.	
Kim et al. [100]	Source rating mechanisms are effective interventions to correct users beliefs, whereby expert rating and user article rating are more effective than user source rating. Low ratings and no-ratings have a dispropor- tional stronger effect on user skepticism than high ratings on user trust.			
Kim et al. [101]	Controversy score that provides additional information of opinions on topics and encourages further exploration can be a more effective tool to combat myth belief than approaches that seek to correct or standardize news opinions.			
Kim et al. [103]			No single strategy ((1) hiding content, allowing for explanations, and option to toggle view, (2) includ- ing an engagement option with the correction that allows for indicator details, (3) Placing agent next to share button that asks for accuracy and reason- ing and presents statistics) was superior over the control. Study highlights necessity of transparency and clarity about intervention's logic and concerns about repeated exposure to misinformation and lack of user engagement.	
Kim et al. [102]	Humorous interventions increase user attention to relevant corrections of misinformation, but non-humorous interventions outperform humor- ous interventions via higher credibility ratings ($n^2 = 0.19$ humor)			
Kirchner and Reuter [104]	Warning-based interventions significantly effect perceived news accuracy but explanation-based approaches are most effective.	Warning-based interventions (with addi- tional explanations) are more effective in correcting user beliefs than less transpar- ent methods such as reduced post size and fact-checks in related articles.		
Komendantova et al. [106]		Stakeholders (journalists/fact-checkers, policymakers, citizens) require design tools for mitigating misinformation and prioritise information regarding actors behind misinforming posts. The most valued features across groups relate to timing and flow of misinformation.		
Koch et al. [105]	Warning labels reduced perceived credibility and lowered self-reported likelihood to amplify fake news (rather small effect).		Removing social endorsement cues (e.g., engage- ment counts) did not have an effect. Did not find a positive effect of warning labels on users' likelihood to elaborate on the fake news post.	
Kreps and Kriner [107]	Compared to no intervention, 'false' tags only have a small effect on users' accuracy assessments while journalistic fact-checks are more effective in reducing misperceptions as well as sharing (independent of partisanship).			
Lee and Bissell [110]			Repeated exposure of myths within corrective infor- mation increased perceived familiarity about misin- formation and increased misinformation credibility (partial η^2 =.02 (effect of correction types on misin- formation familiarity))	

C	Desch i I F Conta		Note for the local sector
Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive
Lee [108]	Web add-on corrections generally decrease the belief in misinformation compared to no correction. For those who are motivated to use social media for specifically for social interaction, narrative corrections are most effective, compared to web add-on's and no corrections (η^2 =0.025 (narrative correction for social interaction-motivated users))		Amongst users in general, narrative corrections are not more effective than web add-on corrections or no corrections.
Lee and Bissell [109]	Both commenting and AI fact-checking labels were effective at promot- ing positive attitudes toward vaccination compared to no intervention. Commenting intervention emerged as promising for suburban partici- pants and the AI intervention was pronounced for urban populations $(n^2=.03$ (for difference in attitudes between three experimental groups))		Neither of the interventions showed salient effects with the rural population.
Liaw et al. [113]		The proposed system utilizes crowd- sourced corrections, such as in-line commentary and corrections which are ranked by the user to enhance compre- hension of news.	
Lillie et al. [114]	The narrative corrective directly reduced misinformation belief com-		
Lim and Per- rault [116]	Post engagement was generally dampened by the presence of warning labels.		Participants were more likely to share congruent posts, with or without labels, suggesting the need for other interventions to address political polariza- tion effects.
Lim and Per- rault [115]	The intent to comment and share was significantly lower for posts with a generic warning label than unlabeled posts. The knowledge, source, and propagation labels encouraged sharing instead. Partisanship effects were observed across the labels (partial $\eta^2 = 0.016$ for effect of warning labels on sharing intentions and 0.0077 on commenting intention)		
Liu et al. [117]	No differences in effectiveness across fact-checking sources (professional fact-checkers, mainstream news outlets, social media platforms, AI, crowd-sourcing; η^2 =0.01) but sources perceived as more credible are more effective		
Lo et al. [118]		Indicates effectiveness of an fake news intervention module that co-works with a news recommendation system and guides users towards verified news.	
Lu et al. [119]			AI label nudges people into aligning their veracity belief in the news with the AI model's prediction regardless of its correctness compared to a control group (Control vs. AI-before: d= 0.17; Control vs. AI-after: d=0.15)
Martel et al. [120]			Hedging corrections or providing increased ex- planatory depth in corrections of misinformation had no impact on engagement with corrective mes- sages on social media.
Martino et al. [121]		The Prta system raises awareness about the use of propaganda techniques in the news, promoting media literacy and crit- ical thinking.	
Mena [122]	A warning label was effective in reducing the intention of a user to share misinformation on Facebook compared to a user who did not see the warning. (d=0.36)		
Moon et al. [125]	Al and user consensus (vs. human experts) source labels reduced partisan-based motivated reasoning in assessing fact-checking mes- sage credibility (η^2 =0.0018 for pattern of motivated reasoning varied by fact-checking sources)		
Moravec et al. [126]	System 1 (automatic cognition) and System 2 (deliberate cognition) interventions both were effective and intervention combining both was twice as effective.		

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Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive
Nekmat [127]	A fact-check alert was effective in reducing likelihood of sharing misin- formation compared to non-exposure.		
Ozturk et al. [129]	A textual counter presented to a rumor was effective in decreasing the likelihood of sharing a tweet compared to the rumor only and rumor with information condition.		
Papakyriakopoulo and Goodman [131]	s Textual overlap in labels reduces user interactions and stronger rebuttals reduced toxicity in comments.		Label placement did not change propensity of users to share and engage with labeled content but falsity of content did.
Pareek and Goncalves [132]	Credibility disputes raised by one's co-partisans significantly reduced belief in misinformation, irrespective of one's relationship closeness with the peer. A peer's knowledgeability may be more potent than trust- worthiness in causing belief change, and trust can sometimes manifest even in the credibility judgement of distant peers, when perceived to have expertise or a fact-checking tendency.		
Park et al. [133]	When opposite fact-checking labels are shown, users who initially dis- approve of a claim are less likely to change their views than those who initially approve of the same claim.	User interviews revealed that users are more likely to share claims with a Di- vided Evidence label than those with a Lack of Evidence label.	
Pasquetto et al. [134]	Audio files on WhatsApp were found to be more effective than text or video-based sources in correcting beliefs about misinformation and they were shared more frequently when communicated by someone close to the user.		
Pennycook et al. [135]	Warnings were effective in a modest reduction in perceived accuracy of false headlines, particularly for politically concordant headlines, relative to a control condition.		The presence of warnings caused untagged head- lines to be seen as more accurate than in the control, even if they were false.
Pennycook et al. [137]	Simple accuracy reminders before sharing information on social media are effective in increasing truth discernment in participants' sharing intentions compared to a control group (d=0.142)		
Pennycook et al. [136]	Shifting the attention of the users on the accuracy of information can encourage them to share higher quality news (e.g., Pearson's $r=0.71/0.67/0.61$)		
Pillai and Fazio [139]	Participants were less likely to share talse headlines in the explain prompt condition compared to control group (exceeded the necessary number of participants according to a priori power analysis; $n^2 = .03$)		
Pluviano et al. [140]			Displaying a myth about vaccines causing autism alongside a factual correction resulted in an in- crease in belief in the myth over a 7 day time period (partial η^2 =0.175)
Porter et al. [141]	Corrections eliminate effects of misinformation on beliefs about vaccine. Effect is robust to formatting changes in the presentation of corrections. Corrections without any formatting modifications are effective at reduc- ing false beliefs with formatting variations playing a very minor role (fact-checks increase accuracy by 0.41 scale points on a four-point scale regardless of formatting; modifications to formatting increase accuracy only by 0.03 points.)		
Porter and Wood [142]	Fact-checks are effective in increasing factual accuracy on realistic sim- ulations of social media platforms (Study 1 Correction Effect d=0.55; Study 2 d=0.79)		
Pretus et al. [145]	Adding a misleading count next to the like count reduced participants' reported likelihood to share inaccurate information by 25% compared to control condition. It was five times more effective as an accuracy nudge (misleading count compared to no intervention: d=0.20; misleading count compared to accuracy nudge: d=0.13).		

Source	Beneficial Effects	Beneficial Percentions	Not effective / counterproductive
Source		Beneficial Perceptions	Not effective / counterproductive
Prike and Ecker [147]	The social-norm intervention reduced belief in false claims and im- proved discrimination between true and false claims. It also had some positive impact on social media engagement. Credibility badges led to greater belief in true claims, lower belief in false claims, and improved		
	discrimination. The credibility-badge intervention also had robust posi- tive impacts on social media engagement. leading to increased flagging		
	and decreased liking and sharing of false posts. Credibility badges and social norms can be effective interventions for counteracting online mis- information. Credibility badges were associated with larger effect sizes		
	(partial $n^2 = 0.09$ (credibility badge) and 0.01 for social norm.)		
Qian et al. [148]	Active interventions significantly increased intention of using reverse image search tools compared to passive interventions and a control		Neither passive nor active interventions had an ef- fect on credibility judgment or misinformation dis-
Rich and	group.		When correcting misinformation, there was no evi-
Zaragoza [150]			dence that the time of correction mattered for the efficacy of the correction and the participants cor- rected beliefs were not durable (durability of cor-
			rected belief η^2 =0.43; time of correction η^2 =0.02)
Ruffin et al.	Simply highlighting and explaining manipulation in photos was not		Intervention was not always effective. Explanation
[155]	aways enective but when it was, it did help make users less agreeing with intended messages (e.g., β =-0.58 of linear regression model for explaining the manipulation versus seeing the original image).		subject/image
Sakhnini and Chattopadhyay [155]		Fact-checking apps should be sensitive to age-related, personal, and political biases	
Saltz et al. [157]		Findings suggest strong emotional reac- tions to misinformation labels in general, which are perceived as overly paternalis- tic, biased, and punitive.	
Sangalang et al. [159]	Narrative correctives (with or without emotional ending) can effectively reduce misinformation beliefs, while emotional corrective endings are better at correcting attitudes.		
Schaewitz and Kramer [160]	Detailed corrections presented alongside disinformation are more effective in better remembering facts compared to simple corrections (η^2 =0.02)		The influence of detailed corrections on personal beliefs regarding the topic of the disinformation is counterproductive as more details in the correction seem to raise readers' concerns when corrections are presented together with the disinformation.
Scharrer et al. [161]	Warnings on top of a scientific message made laypeople hesitant about uncritically and confidently accepting the message as true. Participants agreed less with the claims and deemed the text to be less credible than without the warning $(n^2=0.48)$		Warnings cannot reduce or prevent boost in persua- siveness of easily understandable misinformation.
Schmid et al. [163]	whiled the warming (j =0.10)	A web app based on Social Network Analysis could effectively provide an overview of potentially micleoding ye	
		non-misleading content on Twitter, which can be explored by users and enable foundational learning.	
Schmid and Betsch [162]	Text-based refutations effectively reduced belief in misinformation and immunized participants against impact in short-time (final power of 94.5% was reached to detect a small effect size. Credibility judgment after 2 months was slightly lower (d=0.04)	Unintended effects: lacking effect on in- tentions, backfire-effects among religious groups, biased judgments when omitting information about vaccine side effects	
Seo et al. [165]	Machine-Learning-Graph warning, indicating Source Reliability, Con- tent Truthfulness and Picture/Video Truthfulness, was effective in- creased participants' sensitivity in differentiating fake from real news. $(\eta^2=0.018)$	anomation about valent side circus	
Sharevski and Zeidieh [168]			Warning labels as visual frictions are not accessible for low vision or blind users.

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Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive
Sharevski et al. [166]		SPAM warning tags are promising and in- crease trust in soft moderation. Text-only variant tells participants more of what is going on and a text-and-flag variant gives more specifics and is tougher to refute as a large visual cue. Warning tag with improbable interpretation of facts (FFS) gave convincing options for users to pick why the context is fitting to the misin- formation tweet. Left- and right-leaning participants positively rated the interven- tion.	
Sharevski and Gover [167]			The utterance of a warning cover before a Tweet containing valid information about COVID-19 vac- cines by Alexa will not reduce the perceived accu- racy of the spoken back Tweet's content relative to a no warning cover condition (d=0.018)
Sherman et al. [170]	A combination of expert and user insights is effective in defining inter- pretable warnings and design guidelines for communicating the prove- nance of video content to end-users.		results raise concerns around the potential for users to overgeneralize misinformation warnings regard- ing video or text information
Smith and Seitz [174]	Corrective mock Facebook news feeds were effective in reducing belief in neuroscience myths when shown immediately after the misinformation for those who held incorrect beliefs at pretest.		If participants held correct beliefs at pretest, a sin- gle exposure to misinformation (even when imme- diately corrected) was enough to have a negative impact on their beliefs.
Song et al. [175]	Image-only modality triggered significantly lower levels of message elaboration and heightened message credibility and increased engagement intentions (effect of evidence type on self-reported message elaboration: η^2 =0.01. Effect of presentation mode on message elaboration: η^2 =0.02)	Presence of statistical evidence in asser- tions reduced message elaboration and effects of message in correcting misper- ceptions, decreased perceived message credibility and lowered intentions to fur- ther engange with and disseminate the corrective message	
Sullivan [177]		corrective message.	Libraries were not effective in correcting miscon- ceptions about the flu vaccine through comments
Tanaka and Hi- rayama [178]	Objective countermessages reduced belief in rumors and subjective coun- termessages strengthened false beliefs (e.g., η^2 =0.02. Post-hoc power analysis revealed adequate G*Power >0.80 at medium to large effect size levels).		Subjective countermessages even strengthened false beliefs
Tanaka et al. [179]	Displaying criticism of false information prior to rumors during a dis- aster response is effective in increasing proportion of responses aimed at stopping the spread of rumors compared to displaying the criticism after the rumor.		
Tao et al. [180]	All three types of corrections improved belief accuracy. Corrections incorporating hope appeals showed enhanced effectiveness when threat information was present in comparison to absent hope appeals (Power analysis reveals study can detect small effect sizes (f=0.11) with power of 80%. Hope appeal when threat was present versus absent: n^2 =0.01)		
Thornhill et al. [182]	BalancedView, a proof-of-concept that shows news stories relevant to a tweet suggests that nudging users by providing context information may change the behavior of them towards that of informed news readers.		
Tseng et al. [183]	Corrective information in the form of fext, images, or videos is effective in reducing participants' perceived credibility and potential action for misinformation, with videos being particularly effective in correcting text-based misinformation.		
Tsipursky et al. [184]	The Pro-Truth Pledge (PTP) has been shown to effectively reduce the sharing of misinformation and encourage truthful behavior on social media (d=-1.93).		

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Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive
Tulin et al. [185]	Truth sandwich in fact-check had indirect benefits such as more posi- tively perceived intentions of fact-checkers and less reactance to reading subsequent fact-checks compared to classic fact check that repeats false claim (small effect sizes, e.g., for classic fact-check: β =13		Truth sandwich was not effective in correcting false beliefs but had indirect benefits.
Tully et al. [186]	Users tend to provide accurate information in corrections, particularly after viewing other corrections. However, users are generally unlikely to respond to tweets containing misinformation (exposure to corrections: $\eta^2 = 0.001$; tone of corrections: $\eta^2 = 0.010$).		neither exposure to corrections nor tone of correc- tions increases the self-reported likelihood of re- sponding to the misinformation tweet as compared to the misinformation-only condition
Tully et al. [187]	News literacy messages alter misinformation perceptions, however not with a single message (e.g., partial η^2 =.0.006 for NL tweet leading par- ticipants to rate stories overall as less credible than texting tweet)		
van der Meer			Warnings can prime general distrust in authentic
van der Meer and Jin [189]	Corrective information is effective in debunking misinformation, and factual elaboration compared to simple rebuttal stimulates intentions to take protective action, with government agencies and news media being more effective in improving belief accuracy compared to social peers.		
Velasco et al. [190]		The browser extension that allows to in- sert text and creates a (binary) feedback based on logistic regression was rated highly acceptable in terms of functional- ity, reliability, usability, efficiency, main- tainability, and portability.	
Velez et al. [191]	Fact-checks undo effects of misinformation on beliefs (large and sig- nificant effect of over .26 scale points change). No Backfire effect was observed.		
von der Weth et al. [192]	Nudging users toward more conscious posting and sharing behavior by using linguistic analysis to infer the factuality of content and the credibility of sources is effective in reducing the reach and speed of spread of misinformation		
Vraga et al. [196]	User corrections of a meme containing misinformation are effective in re- ducing the credibility assessment of the misinformation post (η^2 =0.077) and misperceptions (η^2 =0.088)		Exposure to news literacy messages did not enhance the effectiveness of corrective responses or boost NL attitudes and may have generated cynicism.
Vraga and Bode [193]	Social corrections providing a source are effective compared to not giving a source (partial $n^2 = 0.035$)		
Vraga and Bode [197]	Misinformation correction by expert group is effective without loosing the groups credibility and trustworthiness in the context of a health topic (misinformation correction: partial η^2 =0.009; trustworthiness: partial η^2 =0.001; credibility: partial η^2 =0.004)		misinformation corrections of a single user is not effective
Vraga et al. [198] Vraga et al	Expert organizations can be effective in successfully correcting misin- formation on social media on two controversial health topics User corrections in real-time partially reduce the effect of misinforma-		
[194]	tion videos on beliefs (partial η^2 =0.03 compared to no intervention) but not on intentions.		
Vraga et al. [199] Vraga et al	Logic-based and humor-based rhetorical corrections reduce mispercep- tions only for some topics (partial η^2 =0.013).		
[195]	ter the misinformation) corrections reduce misperceptions, with logic- focused corrections appearing to reduce the credibility of misinforma- tion and fact-focused corrections being more credible.		
Wahlheim et al. [200] Waltanharra	Reminders of misinformation are effective to diminish the negative effects of fake-news exposure short-term ($d=0.29$)		
et al. [201]	belped users contextualize posts, identify political tendencies, distin- guish humor from problematic mindsets (qualitatively measured)		

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Source	Beneficial Effects	Beneficial Perceptions	Not effective / counterproductive
Wang and	One sided narrative messages are more effective then two-sided ones		Effect disappeared if participants had smoked e-
Huang [204]	for correcting misinformation on e-cigarettes		cigarettes before
Wang [202]	Participants accept unwelcome fact-checks on Facebook but welcome		
	fact-checks on Line (private messaging app). Fact-checks help increase		
	media literacy in open platforms and hamper media literacy in private		
	messaging apps.		
Westbrook et al.	External correction (news source labeling misinformation as false) in-		
[207]	fluences perceptions of misinformation source. Perceptions of the mis-		
	information source can cause changes in belief in misinformation. (a		
	priori power analysis allowed for desired power of 0.8)		
Wijnker et al.	All investigated correction methods for misleading graphs were effective		
[208]	for debunking misinformation directly after correction and reduces over		
	time. Showing an accurate alternative graph was more effective than		
	visual cues or text-based warning cues to activate graph literacy or		
	warning messages for possible deceit.		
Wood et al.	Debunking messages of healthcare professional lead to increase in be-		
[210]	liefs about risks of vaccines in the UK but not the US. Messages from		
	political authorities and discrediting messages had no effect. There is a		
	joint importance of message source and messaging strategy regarding		
	effectiveness of debunking (e.g., debunking by health experts reduced		
	belief that vaccines cause severe side effects by 0.19 points on Likert		
	scale)		
Zade et al. [214]		Tweet trajectory (e.g., unfamiliar activ-	
		ity invokes skepticism in following net-	
		work) and contextual cues (e.g., profile de-	
		scription helps infer purpose of account)	
		helped support users in assessing credi-	
		bility (qualitatively evaluated).	
Zhao [217]	Participants exhibit a more positive attitude towards corrective messages		
	and have higher vaccination certainty when such messages are present		
	across multiple social media platforms, as opposed to only one platform.		
Zhang et al.	Concise corrections are more effective than exhaustive ones. Graphical		Textual explanations for why misinformation is
[216]	explanation has small positive effect (e.g., Spearman's ρ =0.126).		wrong do not significantly affect effectiveness.
			Warnings in a tough tone make corrections worse.
			Textual and graphic warnings have negative associ-
There are a set of the	Number of the second intervention limbing in spin's for the		ations with correction effectiveness.
Ziteng and Ma	Explanatory annotations and interactive linking in misinformation com-		
[210]	bining text and visualizations can significantly lower perceived credi-		
	Dility (e.g., a=-0.367). The effect to raise awareness is limited/marginal		
	while linking was more effective than annotation (e.g., d=-0.367)		