怀旧对创新技术反应的双刃剑模型

论文复现

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我们的目标论文

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怀旧

More Than a Barrier: Nostalgia Inhibits, but Also Promotes, Favorable Responses to Innovative Technology

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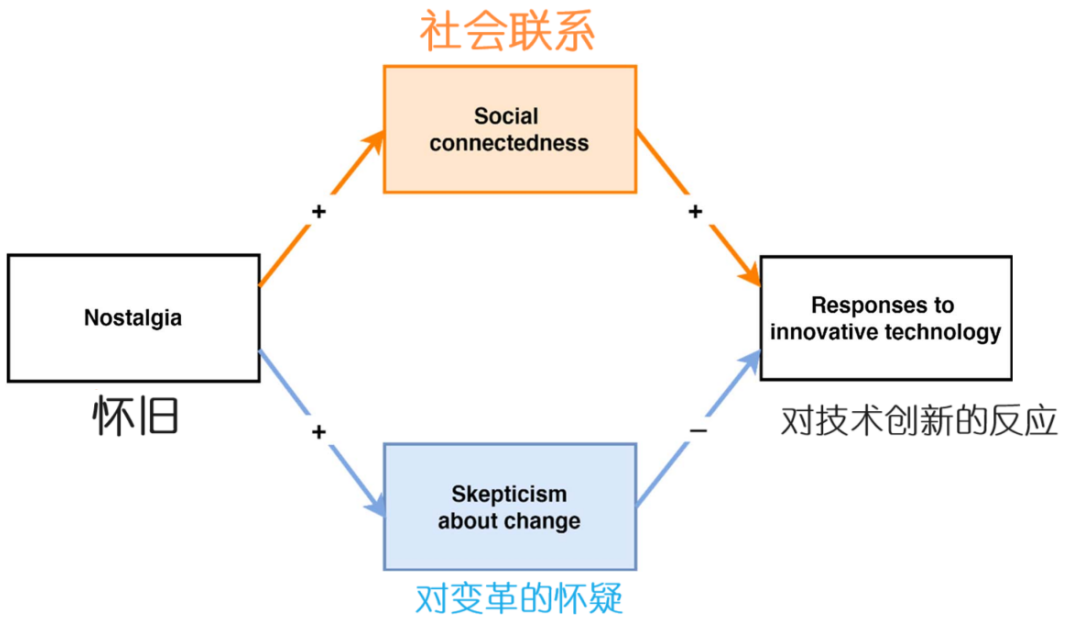
双刃剑模型

文章提出一个双刃剑模型**捕捉**怀旧的双重性:

- 怀旧会通过增加对变革的怀疑来降低对创新技术的好感度。
- 同时，怀旧通过增加社会联系促进了对创新技术反应的好感度。



复现 Study 4

数据

```
library(tidyverse)

rawdat <- haven::read_sav("data/Study 4/Study 4.sav")

d <- rawdat %>%
  rowwise() %>%
  mutate(
    Nostalgia      = mean(c_across(starts_with("NOS"))),
    Skepticism     = mean(c_across(starts_with("SKEP"))),
    Social_connect = mean(c_across(starts_with("SCN"))),
    Support_robot  = mean(c_across(starts_with("SUPPORT"))),
    Adoption_robot =  sum(c_across(starts_with("ADOPT"))),
  ) %>%
  ungroup() %>%
  select(Mnos, Nostalgia, Skepticism, Social_connect, Support_robot, Adoption_robot)
```

Mnos	Nostalgia	Skepticism	Social_connect	Support_robot	Adoption_robot
0	5.33	3.00	2.25	5.33	4
0	5.33	4.75	3.00	4.33	3
1	7.00	3.75	4.50	4.67	0
1	5.33	5.00	5.00	5.00	3
1	7.00	5.25	6.00	5.33	4

Figure 5

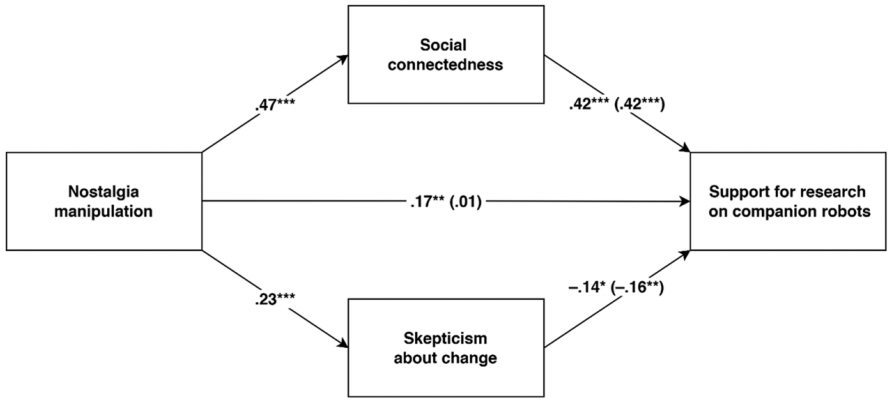
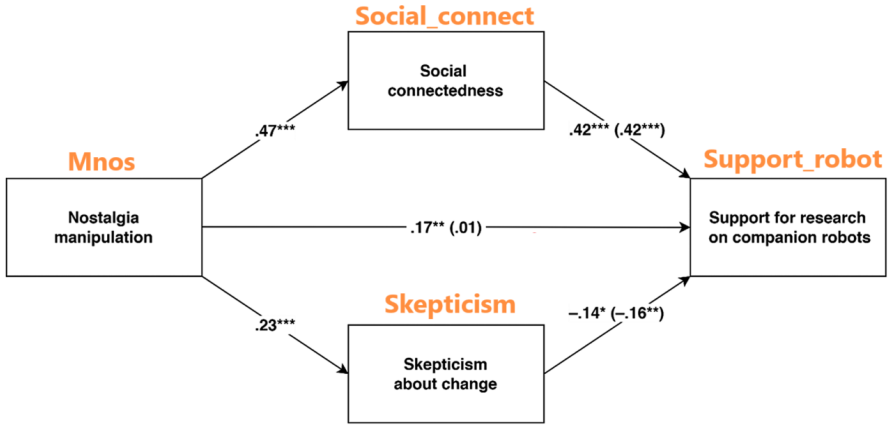

Social connectedness
.47***
.42*** (.42***)
Nostalgia manipulation
.17** (.01)
Support for research on companion robots
.23***
−.14* (−.16**)
Skepticism about change

Figure 5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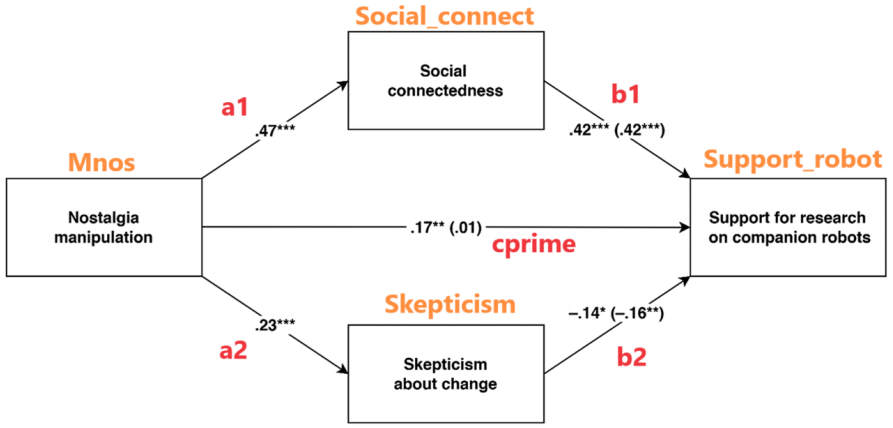
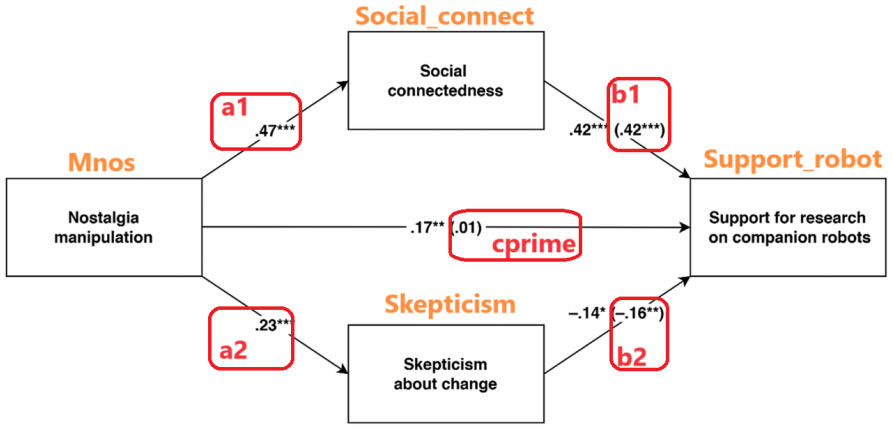



```
library(lavaan)

model <- '

  Social_connect ~ a1 * Mnos
  Skepticism     ~ a2 * Mnos

  Support_robot  ~ cprime * Mnos + b1 * Social_connect +
                   b2 * Skepticism

  # define parameters
  indirect  := a1 * b1 + a2 * b2


'


fit <- sem(model,
           data      = d,
           estimator = "MLR",
           mimic     = "Mplus")
```

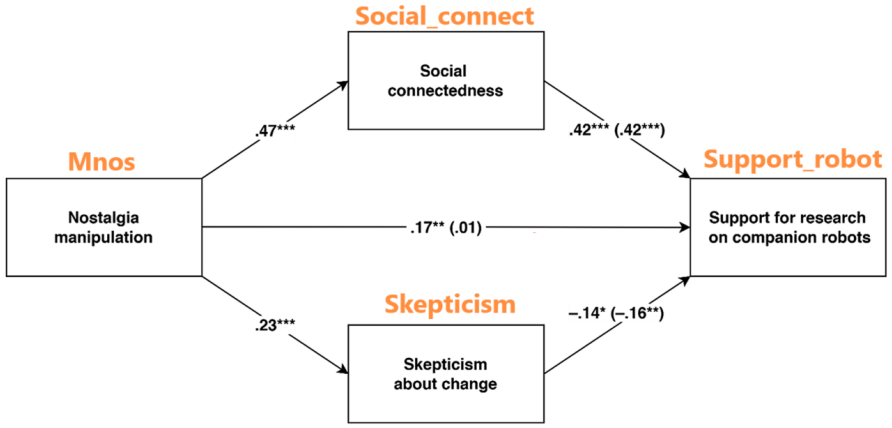
Figure 5



label	estimate	se	pvalue	ci.lower	ci.upper
a1	0.4680	0.0463	0.0000	0.3773	0.5587
a2	0.2251	0.0543	0.0000	0.1186	0.3316
cprime	0.0055	0.0614	0.9291	-0.1149	0.1258
b1	0.4260	0.0517	0.0000	0.3246	0.5274
b2	-0.1603	0.0559	0.0042	-0.2699	-0.0507
indirect	0.1633	0.0355	0.0000	0.0938	0.2328

贝叶斯模型

Figure 5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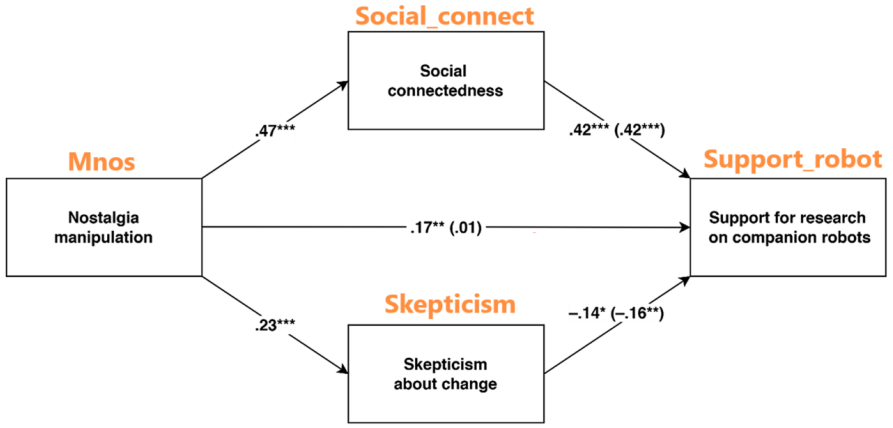


```r
library(brms)

mod <- brm(
  bf(Social_connect ~ Mnos) +
    bf(Skepticism ~ Mnos) +
    bf(Support_robot ~ Mnos + Social_connect + Skepticism) +
    set_rescor(FALSE),

  family = gaussian,
  data   = d,
  chains = 4,
  cores  = 4
)
```

Figure 5

Support for Research on Companion Robots. We specified a saturated model (Figure 5a). Nostalgia positively predicted social connectedness ($b = 1.69$, 95% CI [1.33, 2.05], $SE = 0.18$, $p < .001$, $z = 9.17$, $b^* = .47$), which in turn positively predicted support for research on companion robots ($b = 0.29$, 95% CI [0.07, 0.31], $SE = 0.04$, $z = 7.25$, $p < .001$, $b^* = .42$). At the same time, nostalgia positively predicted skepticism about change ($b = 0.58$, 95% CI [0.29, 0.86], $SE = 0.14$, $z = 4.00$, $p < .001$, $b^* = .23$), which in turn negatively predicted support for research on companion robots ($b = –0.15$, 95% CI [–0.40, –0.20], $SE = 0.05$, $z = –3.01$, $p = .003$, $b^* = –.16$). The indirect effects via social connectedness ($ab = 0.48$, 95% CI [0.35. 0.66]) and skepticism about change ($ab = –0.09$, 95% CI [–0.18, –0.02]) were significant. When controlling for these directionally opposite indirect effects, the direct effect of nostalgia on support for research on companion robots ($b = 0.01$, 95 CI [–0.20, 0.28], $SE = 0.15$, $z = 0.09$, $p = .927$, $b^* = .01$) was not statistically significant.

We also tested the tenability of an equality constraint on the absolute magnitude of the respective indirect effects via social

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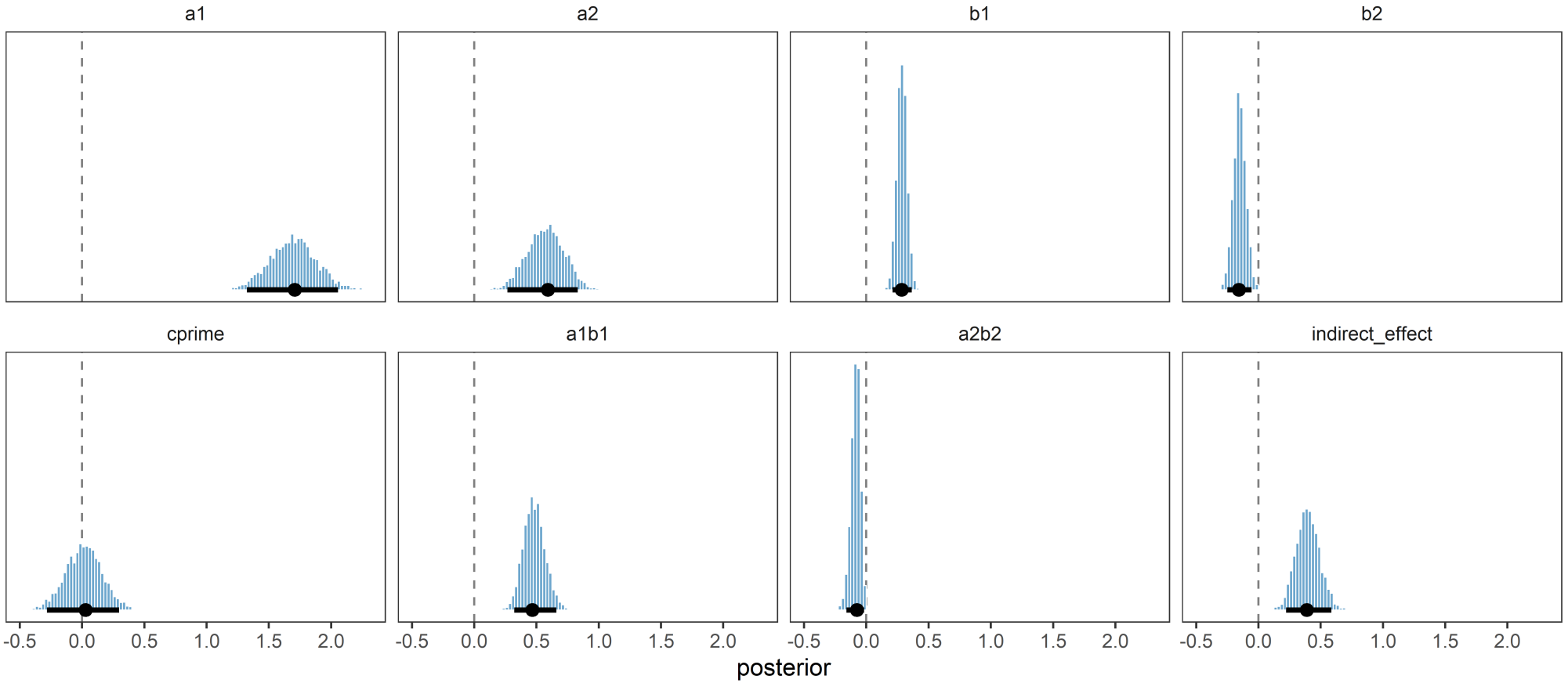
We also tested the tenability of an equality constraint on the absolute magnitude of the respective indirect effects via social

```
draws <- as_draws_df(mod)

draws %>%
  transmute(
    a1      = b_Socialconnect_Mnos,
    a2      = b_Skepticism_Mnos,
    cprime  = b_Supportrobot_Mnos,
    b1      = b_Supportrobot_Social_connect,
    b2      = b_Supportrobot_Skepticism
  ) %>%
  mutate(
    a1b1            = a1 * b1,
    a2b2            = a2 * b2,
    indirect_effect = a1 * b1 + a2 * b2
  ) %>%
  pivot_longer(
    cols          = everything(),
    names_to      = "item",
    values_to     = "value"
  ) %>%
  group_by(item) %>%
  ggdist::mean_hdi(.width = .95)
```

item	value	.lower	.upper	.width	.point	.interval
a1	1.694	1.324	2.056	0.950	mean	hdi
a2	0.572	0.266	0.832	0.950	mean	hdi
b1	0.285	0.211	0.366	0.950	mean	hdi
b2	-0.152	-0.249	-0.054	0.950	mean	hdi
cprime	0.015	-0.282	0.298	0.950	mean	hdi
a1b1	0.483	0.323	0.660	0.950	mean	hdi
a2b2	-0.087	-0.159	-0.018	0.950	mean	hdi
indirect_effect	0.396	0.222	0.587	0.950	mean	hdi

Bayesian interpretation



感谢 R 和 Stan 语言之美!

本幻灯片由 R 包 **xaringan** 和 **flipbookr** 生成