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LONG PAPER

Does my past influence my future? Investigating whether older adults' prior knowledge of one videoconferencing platform transfers to new platforms

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Abstract

Recent years have witnessed a rapid and widespread increase in the usage of online videoconferencing platforms (VCPs), e.g., Zoom, in part due to the COVID-19 pandemic. Older adults, the fastest-growing age group worldwide, are reported to have one of the most significant rates of increase in VCP usage compared to other user groups. To date, research on older adults and VCPs has mostly focused on understanding ways in which VCPs may help to mitigate social isolation and loneliness, and much less on the usability of VCPs among older users. To take steps towards addressing this research gap, this study examined whether, and to what extent, older users' prior usage of a VCP is associated with improved task performance in other VCPs that share similarities in interface layout. Twenty older adults from Canada, New Zealand, the U.K., and the U.S. with experience using the Zoom platform participated in an online study between July 1st and October 1st 2021. In this study, participants completed nine tasks, as meeting participant and host, on three interfaces representing popular VCPs. Task completion time and likelihood were recorded for each platform. Findings suggest that similarity in VCP layouts benefits older adults' task performance on certain platforms. However, degraded task completion likelihood and increased task completion times were observed when older users encountered tasks that were dissimilar from those for which they had familiarity. Our preliminary study findings may offer insights that could help inform the design of VCPs to enhance their usability for older adult users.

Keywords Videoconferencing platforms (VCPs) · Older adults · Transfer of training · Task similarity · Interface layout

1 Introduction

Older adults are the fastest-growing age group worldwide. In 2017, in the United States, approximately 70 million people were 60 years and older, accounting for more than 20% of the population. This number is projected to increase to more than 100 million by 2050 [1]. Over the same time period, a commensurate percentage increase is expected in the proportion of older adults who use new computer and internet-related technologies [2]. A number of factors may explain why more older adults are embracing technology at an unprecedented rate. First, smart technologies are becoming more pervasive throughout society. To a large extent, digital technologies are increasingly being required to use in order to carry out certain tasks, such as shopping, making appointments, and communicating with others. Also, the COVID-19 pandemic forced many older adults to begin using never-before-seen technologies to perform various tasks remotely as opposed to completing those tasks in person. Particularly,

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early on during the pandemic, older adults were advised to stay home and isolate due to potential health concerns [3]. Yet, they still largely needed and desired social interactions.

1.1 Videoconferencing platforms and older users

One particular type of technology designed to enable such communication and social exchanges, and that saw a rapid uptick in usage by older populations, is videoconferencing platforms (VCPs) [4]. Videoconferencing platforms are systems/software that enable two or more people to emulate person-to-person meetings remotely via the internet using real-time, multidirectional video and audio streaming [5]. Some of today's most commonly used VCPs are Zoom, Adobe Connect, Webex by Cisco, Microsoft Teams, and Skype [6]. Other features afforded by these platforms include messaging, content and screen sharing, recording, and scheduling meetings. To date, research on older adults and VCP use has predominantly focused on usage of these systems as a way to reduce loneliness and isolation among older populations (e.g., [7–9]). For example, Siniscarco et al. [9] used Skype to examine the well-being of older adults in long-term care. The researchers found that VCPs were not associated with significant changes in affective well-being. In a different study, Carpenter [7] investigated older adults with normal or mild cognitive impairments living independently to determine whether providing weekly video conferencing sessions with friends and family improve loneliness and depression. This study found significant improvements for older adults with respect to loneliness, depression, and social isolation after the weekly use of a VCP.

While these types of studies provide important information regarding how VCPs can potentially be used to mitigate negative (mental) health outcomes in older adults, there is a need to understand how older users actually carry out tasks on VCP interfaces. This is because aging is associated with many perceptual and psychological changes as well as generational differences in experiences and expectations that could create challenges for older adults interacting with technology [10]. Many commercially-available VCPs exist and not all older individuals use the same system. The particular software they use is often driven by the purpose of use, accessibility, and other persons/parties involved in the communication scheme. Although most VCPs generally provide the same utilities, they differ in terms of their specific feature arrangements, informational structures, and layouts. For example, chat or messaging functions are supported by most VCPs, yet the location, presentation, and labeling associated with this particular feature is different across platforms. The Zoom and Google Meet VCPs illustrate this difference. The location of the chat box in Zoom is located on the bottom left of the user interface and is labeled 'chat,' while the chat feature in Google Meet is an icon located on the bottom right of the screen. This example highlights the need to empirically determine whether transfer of training, or improved performance on a new task as a result of previous experiences associated with an older different task, exists in older adults across various VCPs [11]. This knowledge is currently absent from the literature on aging and videoconferencing platform use, but could significantly help determine whether familiarity with any one VCP can more easily aid older adults in independently learning and using other VCPs.

1.2 Transfer of training

Previous studies infer that prior experience using one technology can positively impact performance when using a new related technology. For example, Singley and Anderson [12] conducted a study with 24 participants aged 18–30 years to examine learning and knowledge transfer in text editing. At the beginning of the study, participants were taught the minimum core set of commands needed to use the line text editors, which served as their baseline knowledge. Over the course of six days, they edited the text. During the first two days, they used a line-based editor (ED), a different line-based editor (EDT) over the next two days, and a screen-based editor (EMACS) during the last two days. The results showed that there was a moderate amount of transfer of training from the line-based editors to the screen-based editors. Similarly, Slegers et al. [13] investigated the effects of computer training and usage on 240 older adults who were non-active users of personal computers (PCs). Two-thirds of the older adults participated in an initial training session, where they could voluntarily practice with a PC and its operating system, use a word processor, browse the internet, and use the email interface. Results of a technological transfer assessment after 12 months showed that the group who received training and frequently used a PC for daily tasks was faster and more accurate in conducting new voice menu tasks and the alarm clock tests on a PC compared to the control group who refrained from using a PC for 12 months. Older users did not receive direct training on these particular tasks. Instead, their knowledge of these tasks and how to perform them was developed as a result of their general daily usage of a PC over the 12-month period, suggesting that a positive transfer of training occurred.

One important factor known to contribute to a positive transfer of training in task performance is the similarity of tasks and/or layout of information. Czaja and Sharit [11] explain that from a stimulus–response perspective, if the new stimuli are similar to the ones previously encountered and the responses to these stimuli remain relatively the same, then a high positive transfer of training will occur. Wickens [14] highlights that familiar icons, actions, and procedures from some displays that are designed in a consistent manner will easily transfer to support processing of new displays. Also, Taatgen's primitive information processing element (PRIM) model [15] adds that the use of working memory to copy an element received from a visual module from one place to another in a workspace is a deterministic factor of transfer task performance. To this end, transfer effects can be attributed to information cues that directly trigger user input as well as information coding that helps to retrieve information from the memory [11]. As evidence of transfer occurrence, studies have used improved task performance measures, such as reduced task completion time and higher task response correct rate [16]. Singley and Anderson [17] explain that when task completion time is reduced due to a positive transfer of training, the effect is mostly associated with a reduction in planning time as opposed to execution time. But, while the transfer of training has been demonstrated for some tasks and technologies in older users, to date, no empirical data is available regarding whether a positive transfer of training is possible in older adults for various tasks on videoconferencing platforms, which represent a persuasive technology in today's society.

1.3 The present study

This study aims to take initial steps to fill the critical gap in the research literature regarding whether previous experience with one videoconferencing platform can lead to improved task performance in other VCPs for older adults. Additionally, we intend to understand the extent to which similarity in interface and task structures between familiar and new tasks moderate performance on the new task**.** To answer these research questions, we developed an online experiment, during the COVID-19 pandemic, wherein older users with experience in using the Zoom platform (as participants in the meeting) were asked to complete common tasks on two unfamiliar VCPs that share different levels of similarities with Zoom. Generally, older adults are known to apply information learned from previous environments to navigate new, but similar environments [10]. Thus, we expected improved task performance, such as reduced task completion time, on tasks that are more similar to those in which participants already have experience performing (specific hypotheses are included in Sect. 2.4). The results of this study can help researchers better understand how previous experience and task similarity affect task performance. Findings can also provide quantitative insights that guide researchers and designers in considering ways to refine various pervasive technologies that support older adult users in learning independently and building technological self-efficacy.

2 Method

2.1 Participants

Twenty older adult participants were included in this study. Participants were between the ages of 60 and 88 years (M = 65.55 years, SD = 6.39), and were all recruited via the Amazon Mechanical Turk (MTurk; www.mturk.com) and Prolific (www.prolific.co) crowdsourcing platforms. This study was conducted during the COVID-19 pandemic, thus both venues were used for recruitment as a way to increase the likelihood of identifying older adults who met our eligibility requirements. All participants were native English speakers (1 Canada, 2 New Zealand, 1 U.K. and 16 U.S.) and were required to have prior experience participating in a Zoom meeting for a minimum of eight times in a calendar year (for any length of time). This approximates using Zoom more than once every two months. This requirement was set to ensure that participants would already be familiar with conducting participant-related tasks in Zoom and had developed some degree of automaticity. This requirement would also allow the research team to examine whether transfer exists as participants face new tasks and new design [18]. Participants did not have experience with the other two platforms. At the end of the study, they received a one-time payment of $4, which is higher than the average pay rate for similar studies conducted using crowdsourcing platforms [19]. The demographic information of the participants is provided in Table 1. This study was approved by the Purdue University Institutional Review Board (Protocol: IRB-2020-1406) and was conducted according to the American Psychological Association (APA) Code of Ethics.

2.2 User tasks

Three popular and commercially-available videoconferencing platforms were included in this study. They were labeled by the researchers as Platform A (Zoom), B, and C to preserve confidentiality. These particular platforms were chosen because they are among the most commonly used VCPs, to date. Participants were asked to complete a series of representative tasks using all three platforms during a fictitious web meeting consisting of de-identified interactive (identical) replicas of each VCP interface. Mock interfaces of all three VCPs were developed by the research team using Python and hosted on a GitHub site. In particular, screenshots of each platform were taken and used to construct life-size replicas of each platform and its associated features. However, none of the companies' logos were visible. Also, only major components of the

Table 1 Demographics of participants

Demographic factors	N
Sample size (*N*)	20
Gender	
Female	11
Male	9
Ethnicity	
African/African American	1
Asian	1
Caucasian	16
Hispanic Latino	1
Other	1
Country	
Canada	1
New Zealand	2
United Kingdom (U.K.)	1
United States (U.S.)	16
Age (years)	
60–64	8
65–69	8
70–74	3
75–79	-
80 and up	1
Education	
Some high school	1
High school graduate	2
Some college/Associate degree	4
Professional degree	1
Bachelor's degree	7
Master's degree	4
Doctoral degree	1
Working status	
Volunteering part time	1
Volunteering full time	1
Working part time	3
Working full time	6
Retired	9

tasks of interest (see Table 2) were interactive, such that a mouse click made by the participant would result in an actual change in the information displayed on the screen.

All platforms support both host and participant tasks/roles. *Host* tasks are those in which the person leading and/or managing the meeting has the authority to conduct, such as scheduling a meeting and accessing existing recordings. In contrast, *Participant* tasks are those that attendees of the videoconference are allowed to perform, such as messaging and initiating screen share. In this study, all participants were asked to perform both *Host* and *Participant* tasks in order to gain a more comprehensive understanding of how older adults perform task globally on these platforms. Each participant completed a total of nine distinctive tasks (i.e., 4 *Host* tasks and 5 *Participant* tasks) on each of the three VCPs (Table 2). These particular tasks were chosen as the result of a feature audit conducted by the research team, and were deemed to be common and representative tasks for a day-to-day VCP user. Each participant in the study performed both *Host* and *Participant* tasks in a counterbalanced order, thus minimizing potential learning effects.

2.2.1 Platforms

The general layouts of the three platforms are depicted below in Figs. 1, 2 and 3, showing the main meeting user interface for both *Host* (right) and *Participant* (left) tasks. The host and participant user interfaces were divided into major sections based on the functions/buttons shown on the main user interface, their locations, and their prevalence. This separation was done to visualize the similarities of elements within the platforms and to directly examine consistency among the interfaces.

The three fictitious interfaces were used for the data collection for the study and the task completion time for each task was recorded. Task completion time was defined as the time between when the task interface was first displayed and when the participant clicked the correct location that would result in the execution of the target function. Also, each observation was labeled as complete or incomplete, depending on whether or not the participant completed the given task within the required timeframe (60 s), beginning from when that particular task was first displayed. This data was used to estimate the task completion likelihood.

Table 2 Summary of tasks

Host (H) tasks	Participant (P) tasks
H1: Select a recorded meeting	P1: Un-mirror your video camera
H2: Select a past meeting	P2: Replace your background with a virtual background
H3: Schedule a meeting	P3: Switch the audio outlet from computer to phone
H4: Automatically mute participants when they login	P4: Send a message to all participants in the chat
	P5: Share your screen

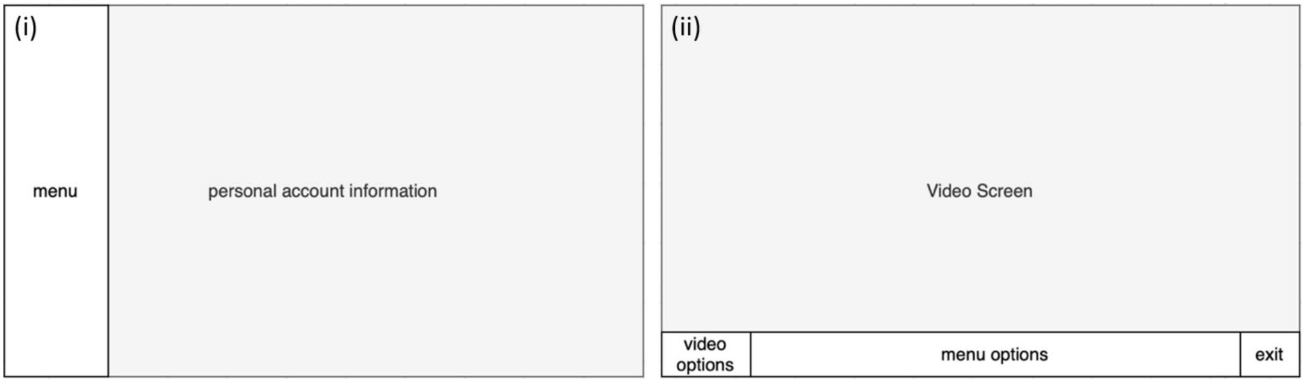

Fig. 1 Platform A (Zoom) host (i) and participant (ii) interface layout

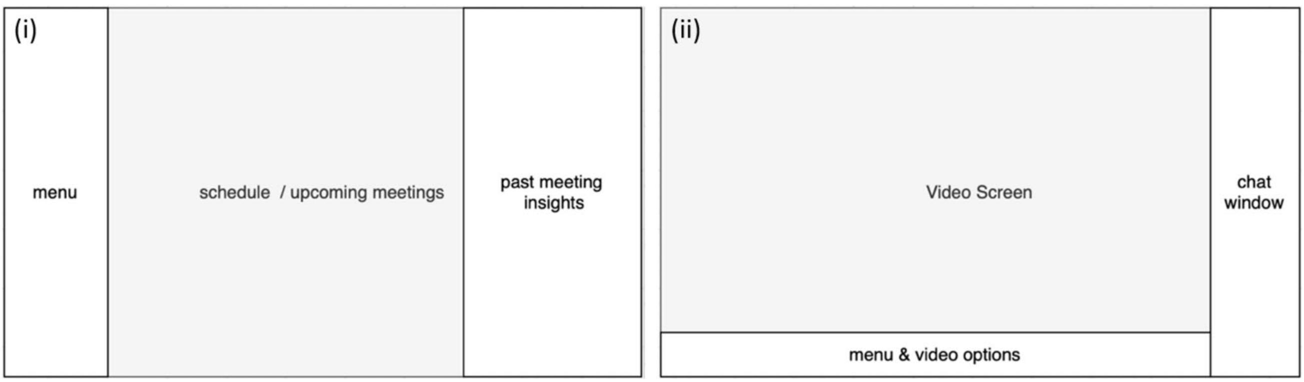

Fig. 2 Platform B host (i) and participant (ii) interface layout

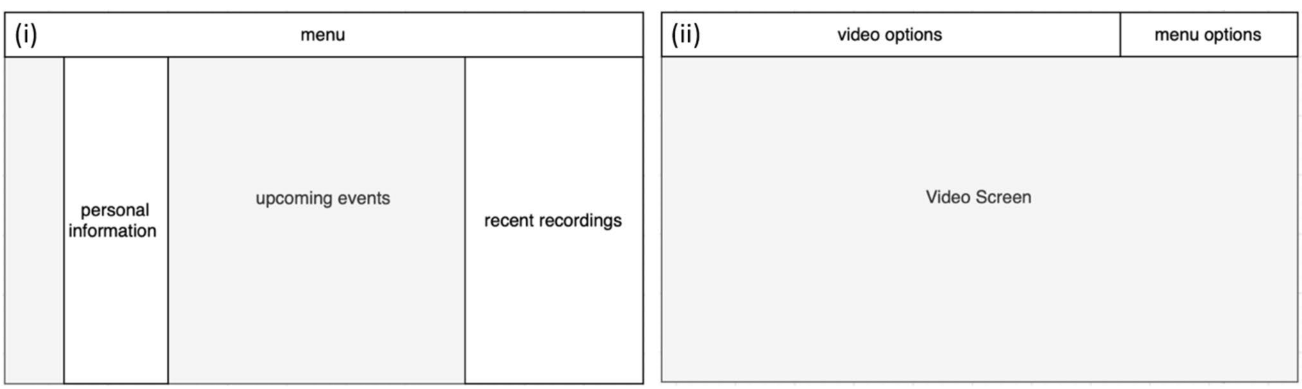

Fig. 3 Platform C host (i) and participant (ii) interface layout

To evaluate the effects of previous experience on task performance, the nine tasks were grouped by their similarities in **User Role** and by **Information Structure**.

2.2.2 User role

For user roles, tasks were grouped as *Host* (H1- H4) or *Participant (P1-P5)*. Since all participants had previous experience using *Platform A* (Zoom) as a participant, we hypothesized that participants would have better performance on *Participant* tasks (P1–P5) in *Platforms B* and *Platform C*, compared to *Host* tasks (H1–H4).

Differences in user roles are mainly related to the layout of the main user interface. For example, all *Participant* tasks (P1–P5) were initiated from the meeting homepage, where the 'video screen' is shown (Figs. 1, 2, 3). In general, the layout of the meeting homepages is considered to be similar across all three platforms, given that the meeting and menu options are located either on the top or button of the screen, where the video screen consumes the vast majority of the interface. On the contrary, the *Host* tasks (H1–H4) were initiated from different setting pages that share far fewer commonalities in terms of the overall layout and location of functions. More specifically, *Host* tasks have different functions on the main screen, with the menu bar being the only component that is always visible in all platforms. Other functions, such as accessing user profile and past/upcoming meetings and recordings, are all accessible from different menu options across the three platforms (Figs. 1, 2, 3).

2.2.3 Information structure

While the user role is mostly associated with the general layout of the user interface, another aspect of task similarity relates to how the user navigates to a specific function. Previous studies have shown that appropriate schemas of information structures, such as menu navigation, support user tasks [20]. Furthermore, an adequate mental representation of the data structure of a platform was a decisive factor for navigation performance, especially for an older adult user group [21].

In this study, participants' previous experience with Zoom (*Platform A*) was expected to help them establish a mental model of the informational structure of the Zoom interface, which would benefit their performance on tasks on other VCPs that share similar information structures. To determine whether this would be the case, the research team classified all tasks according to their similarity in **Information Structure (IS)**, which accounts for both the navigational structure as well as the (sequence of) steps that users must follow in order to successfully perform the task. We hypothesized that tasks with an information structure similar to their counterparts (in *Platform A*) would be easier for older participants to apply their mental models to navigate and locate specific functions.

To systematically capture differences in information structure and task flow among the three VCPs across different tasks, hierarchical task analyses (HTA) were conducted. This approach is regarded as an effective tool for menu structure design of user interfaces [22] (see results in Appendix 1). Following this method, the research team grouped all user tasks by their similarities in information structure with respect to Platform A, using the following grouping conventions: *IS1, IS2, IS3*.

- *IS1* (Tasks H1, H3, P2, P4): Platforms A, B, and C are similar in information structure.
- *IS2* (Tasks H2, P3, P5): Platform C has a different information structure compared to Platform A and B.
- *IS3* (Tasks H4, P1): Platforms A, B, and C all have different information structure.

In summary, the three factors used in our study to help understand whether transfer of training exists in older adults for VCPs are: a) **Platform** (*Platforms A*, *Platform B*, and *Platform C*), and b) **User Role** (*Host, Participant*) **OR** c) **Information Structure** (*IS1, IS2,* and *IS3*).

2.3 Experiment procedure

The Amazon Mechanical Turk (MTurk) and Prolific crowdsourcing platforms were used to collect demographic information from participants as well as data during the actual study. The study was posted to each platform from July 1st to October 1st, 2021, and volunteers who met eligibility criteria were invited to participate in the study.

Before the start of the study, all participants were asked to first read a statement regarding the purpose of the study, complete the study's consent and information forms, and complete two demonstration tasks. The two demonstration tasks included one participant task (i.e., unmute microphone) and one host task (i.e., select meeting ID) on *Platform A* (Zoom). These tasks were not included in the actual study. The purpose of this demonstration session was to give participants the opportunity to become familiar with the types of tasks they would be performing in the actual experiment as well as the structure of the online experiment. All participants were also required to complete a pre-experiment questionnaire in Qualtrics^{XM}, which queried background information such as age, gender, education, work status, and (general) smart technology usage.

After completing the demographic questionnaire, participants were directed to the study page through a link, where they completed the nine (including *Host* and *Participant*) tasks on each of the three VCPs. Given that the systems were only built to be replicas of the actual three VCPs, participants essentially completed a series of 'search and click' tasks on each mock interactive interface. In other words, the nine tasks only required participants to locate and click on specific areas directly related to task objectives as opposed to interacting with the system freely as they would in real-life. For example, the 'send a message' task (P4) only required participants to click on the chat box, but not actually type nor send a message.

The tasks were presented in a pre-determined, but randomized order. Before the start of each individual task, a white screen with the task instructions written in black and a "Ready" button located in the center of the screen was displayed to the participant. Once participants clicked the "Ready" button, a timer (not visible to the participant) started to count down from 60 s, and the screen displayed the main homepage of either the host or participant interface (which in it, consisted of a correct series of steps/path for executing one of the nine tasks they were asked to complete). For each task, participants needed to click on the area of the screen that corresponded to the appropriate location for the given task within the 60 s time window. Results of a pilot study showed that 60 s was sufficient for participants to complete the specific tasks on each VCP, whether they had previous experience with the VCP or not. Once the correct location was clicked on by participants, the time elapsed was automatically recorded by the program and another white screen with the next task instructions (and a "ready" button) was presented. This same process was repeated until all tasks were complete (9 tasks for each of the 3 platforms = 27 tasks in total). If a participant did not locate and click the correct area/location for a given task within 60 s, the software would automatically progress to the next task screen and the participant's response was recorded as "incomplete." After all tasks were completed, participants would be directed to a post-experiment questionnaire hosted via Qualtrics^{XM}. This questionnaire asked participants about any strategies they used during the experiment and to comment on their perspective on their knowledge transfer. The study lasted approximately 30 min.

3 Research hypotheses

This study aims to investigate whether previous experience with one videoconferencing platform can lead to improved task performance in other VCPs for older adults. The study also seeks to determine the extent to which similarity in interface design and task structures between familiar and new tasks moderate performance on new tasks. Based on these research objectives, we defined the following hypotheses:

H1 Task completion likelihood is higher on *Participant* tasks than on *Host* tasks on unfamiliar platforms (*Platform B* and *Platform C*);

H2 Task completion likelihood is lower on tasks with information structures different from those in *Platform A (IS2 and IS3)* compared to tasks that are similar to those in *Platform A (IS1)*;

H3 Task completion time is shorter on *Participant* tasks than on *Host* tasks on unfamiliar platforms (*Platform B* and *Platform C*);

H4 Task completion time is shorter on tasks with information structures different from those in *Platform A (IS2 and IS3)* compared to tasks that are similar to those in *Platform A (IS1)*.

3.1 Data analysis

A within-subjects design with nine tasks (4 *Host* and 5 *Participant* tasks) on three platforms (*Platform A*, *Platform B*, *Platform C*) was used, resulting in 27 tasks for each participant.

Task completion time was the primary task performance measure. However, if a participant failed to achieve the task objective of an individual task run (i.e., correctly click the target area on the interface) within 60 s, that task run was marked as incomplete and their data for that task was not used in the analysis. Data on the complete and incomplete tasks were to calculate the task completion likelihood.

One challenge for the analysis of our particular data sets is missing data points and a smaller sample size due to some incomplete tasks. As a result, we used mixed effects models to assess the main effects of **Platform**, **User Role,** and **Information Structure** on task performance. Random effects were introduced to account for individual differences among participants and individual tasks. Here, all data points (both complete and incomplete cases) were included for the task completion likelihood model. Only complete cases were included for the completion time model. The Akaike information criterion (AIC) was used to assist with selecting the appropriate statistical model for the final analysis. Also, parametric bootstrap tests were used in place of traditional Likelihood Ratio Tests (LRT) to determine the significance of individual parameters in the final models, given its ability to handle small sample sizes and normality violations.

All analyses were performed using R 4.2.2. Mixed effects binary logistic regression were used to predict task completion likelihood and linear mixed models (LMMs) were used to predict task completion time using the lme4 package [23]. Particularly, for the binary outcome of task completion likelihood (complete or incomplete), mixed effects binary logistic regression was employed. The *lmerTest* package [24] was used and t-tests with Satterthwaite approximation was used for degrees of freedom calculations. The goodness of fit of the models was measured using the conditional pseudo-R-squared using the *sjstats* package [25]. The parametric bootstrap tests were conducted using the *pbkrtest* package [26]. The *sjPlot* package [27] was used to plot the fixed effects estimates and 95% confidence interval in logistic regression models. The *ggplot2* package [28] was used for all other visualizations.

To determine how interaction terms and random effects should be incorporated in the final model for analysis, for each set of fixed effects **(A) Platform + User Role, (B) Platform + Information Structure**, AIC values and parametric bootstrap tests were used to determine whether the full model needed to be modified. The full models included the interaction term between the two main effects as fixed effects, and random intercepts for both subjects and task numbers to account for within-subject correlations and between-task variations.

For both fixed effects sets, the full model was the best fitting model with the lowest AIC and was significantly different than other models at $p = 0.05$ level with the parametric bootstrap tests. These models are expressed as Eqs. 1 and 2, where the subscripts represent the measurement occasions (i) and participants (j), respectively. The models also include the fixed effects intercept β_0, fixed effects coefficients $\beta_1, \beta_2, \beta_3$, and subjective specific random intercepts for both measurement occasions/tasks ($\eta_{I,0i}$) and participants ($\eta_{J,0j}$). Finally, p_{ij} is the probability of task completion.

Equation 1 Task completion likelihood model—Fixed effects set A

$$\log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_0 + \beta_1 Platform_{ij} + \beta_2 Role_{ij} + \beta_3 Platform_{ij}{:}Role_{ij} + \eta_{I,0i} + \eta_{J,0j} + \epsilon_{ij} \tag{1}$$

Equation 2 Task completion likelihood model—Fixed effects set B

$$\log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_0 + \beta_1 Platform_{ij} + \beta_2 IS_{ij} + \beta_3 Platform_{ij} : IS_{ij} + \eta_{I,0i} + \eta_{J,0j} + \epsilon_{ij} \tag{2}$$

Table 3 Parameter estimates of task completion (Platform + User Role)

	Task Completion States (Binary Logistic)		
	Coefficient Estimates (Odds Ratio)	(Z-statistics)	*p*-value
Number of observations	539		
Fixed Effects			
Intercept	1.57	(1.325)	0.185
Platform			
Platform A	(Reference)		
Platform B	0.98	(1.848)	0.065
Platform C	− 1.28	(− 2.623)	0.009**
User Role			
Host	(Reference)		
Participant	− 1.03	(− 0.664)	0.506
Platform x User Role			
Platform B: Participant	− 0.10	(− 0.150)	0.880
Platform C: Participant	1.81	(2.826)	0.005**

$^{\cdot}p < 0.1$, $*p < 0.05$, $**p < 0.01$, $Conditional pseudo R^2 = 0.66$

For task completion time, for both fixed model sets (A) and (B), the full models were the best fitting model with the lowest AIC and were significantly different than other models at $p = 0.05$ level with the parametric bootstrap tests. For task completion time, only the completed tasks, 359 out of the 539 total observations, were analyzed.

4 Results

4.1 Task completion likelihood

4.1.1 Platform + User Role (Fixed Effects Set A)

Table 3 summarizes the results of the binary logistic regression for task completion states, using *Platform A + Host* as the reference. Participants in *Platform C* were found to have a significantly lower likelihood of task completion ($\hat{\beta} = -1.28, p < 0.01$) compared to the reference level. The significant interaction between **Platform** and **User Role** indicates that for *Platform C***,** users in the *Participant* task condition were more likely to complete the tasks compared to when in the *Host* task condition ($\hat{\beta} = 1.81, p < 0.01$). No significant difference in task completion likelihood was found in *Platform B*. Also, task completion likelihood was not significantly affected by **User Role** alone. The standard error is based on a 95% confidence interval of the fitted model (Fig. 4).

4.1.2 Platform + Information Structure (Fixed Effects Set B)

Table 4 summarizes the results of the logistic regression for task completion states, using *Platform A + Information Structure 1 (IS1)* as the reference. A significant negative effect on task completion likelihood was found for *IS3* alone, indicating that when the information structures were very different, the task completion rate was negatively affected, regardless of other factors ($\hat{\beta} = -5.41, p < 0.01$). The standard error is based on a 95% confidence interval of the fitted model (Fig. 5). In addition, to a lesser extent, when the information structures were similar between *Platform A* and *B* (*IS2*), a significant increase in task completion likelihood in *Platform B* ($\hat{\beta} = 2.62, p < 0.01$) was observed.

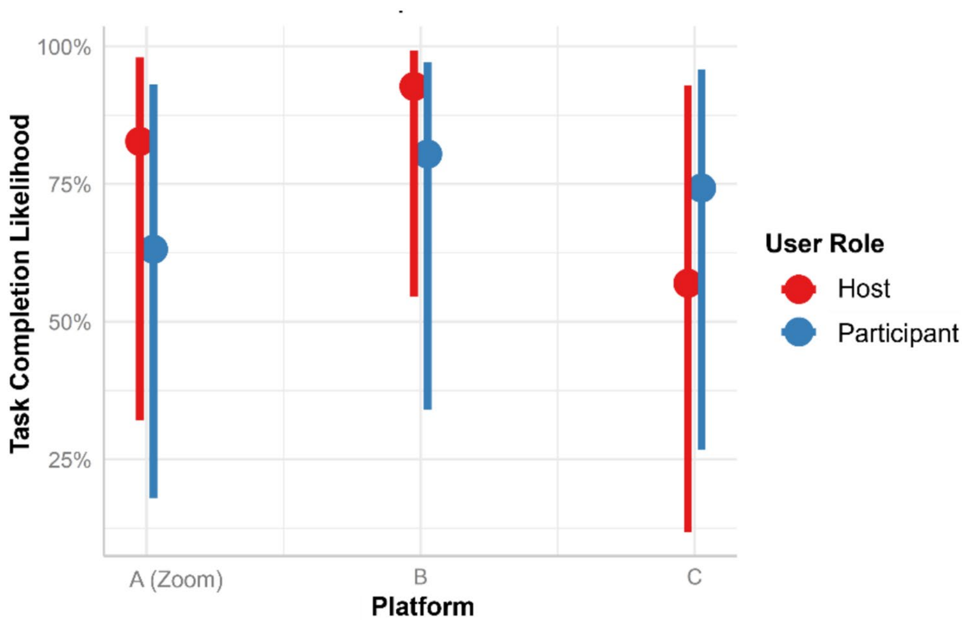

Fig. 4 Estimated task completion likelihood and 95% confidence interval by user role

Table 4 Parameter estimates of task completion (Platform + Task Flow)

	Task Completion States (Logistic)		
	Coefficient Estimates (Odds Ratio)	(Z-statistics)	*p*-value
Number of observations	539		
Fixed Effects			
Intercept	2.37	(3.587)	< 0.001**
Platform			
Platform A	(Reference)		
Platform B	– 0.13	(– 0.259)	0.796
Platform C	0.28	(0.539)	0.590
Information Structure			
IS1	(Reference)		
IS2	– 0.83	(– 0.922)	0.356
IS3	– 5.41	(– 4.819)	< 0.001**
Platform x Information Structure			
Platform B: IS2	2.62	(2.752)	0.006**
Platform C: IS2	– 1.11	(– 1.614)	0.107
Platform B: IS3	1.59	(1.802)	0.071`
Platform C: IS3	0.07	(0.074)	0.941

'$p < 0.1$, *$p < 0.05$, **$p < 0.01$, $ConditionalpseudoR^2 = 0.67$

4.2 Task completion time

Among the 539 total observations, there were 359 completed observations. The task completion analysis was based on the completed observations only.

4.2.1 Platform + User Role (Fixed Effects Set A)

Table 5 summarizes the results of the linear mixed model (LMM) for task completion time, using *Platform A + Host* as the reference. Participants in *Platform B* and *Platform C* were found to have a significantly shorter task completion times ($\hat{\beta}_B = -5.363, p = 0.015; \hat{\beta}_C = -6.342, p = 0.009$) compared to the reference level. This indicates a significant decrease in task completion time for *Host* tasks in the

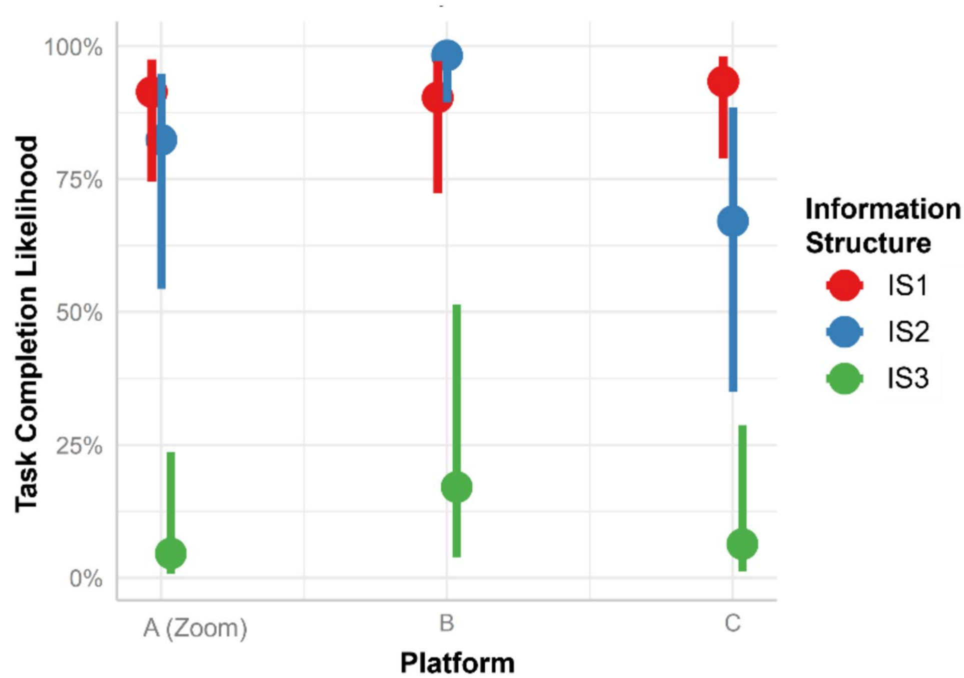

Fig. 5 Estimated task completion likelihood and 95% confidence interval by information structure similarity

unfamiliar platforms (*Platform B* and *Platform C*). The significant interaction between **Platform** and **User Role** indicates that this difference does not hold for *Participant* tasks. When using *Platform A + Participant* as the reference, the effects of **Platform** are no longer significant (Fig. 6). Task completion time was not significantly affected by **User Role** alone. In the model presented in Table 5, the estimated subject variance was 20.74 and the estimated task variance was 53.29. In contrast, the estimated residual variance was 139.61, indicating a relatively moderate within-subject variability (Fig. 7).

Table 5 Parameter estimates of completion time (Platform + User Role)

	Task Completion Time (LMM)		
	Coefficient Estimate	(t-statistics)	*p*-value
Number of observations	359		
Fixed Effects			
Intercept	25.02	(5.99)	< 0.001**
Platform			
Platform A	(Reference)		
Platform B	− 5.363	(− 2.438)	0.015*
Platform C	− 6.342	(− 2.640)	0.009**
User Role			
Host	(Reference)		
Participant	− 3.842	(− 0.700)	0.512
Platform: User Role			
Platform B: Participant	6.936	(2.285)	0.023*
Platform C: Participant	6.818	(2.126)	0.034*

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $Conditional pseudo R^2 = 0.358$

4.2.2 Platform + Information Structure (Fixed Effects Set B)

Table 6 summarizes the results of the LMM for task completion time, using *Platform A + IS1* as the reference. Overall, *Platform C* alone, at the reference information structure level was associated with shorter completion times ($\hat{\beta}_C = -8.61, p < 0.01$). This finding is also highlighted by a significant interaction term, meaning that when the information structures were not similar (as in *IS2* and *IS3*), the completion time on *Platform C* increased dramatically ($\hat{\beta}_{BxIS2} = 17.8, p < 0.01$; $\hat{\beta}_{CxIS3} = 9.75, p < 0.05$), far outweighing its previous reduction in completion time in *IS1*. When considering the effects of task flow similarity on completion time, the estimated subject variance was 43.16 and the estimated task variance was 61.71. In contrast, the estimated residual variance was 233.85, indicating a relatively moderate within-subject variability. A significant negative effect on task completion time was found for *IS3* alone, indicating that when the information structures were very different from one another, longer task completion times were observed, regardless of other factors ($\hat{\beta}_{IS3} = 29.59, p < 0.01$).

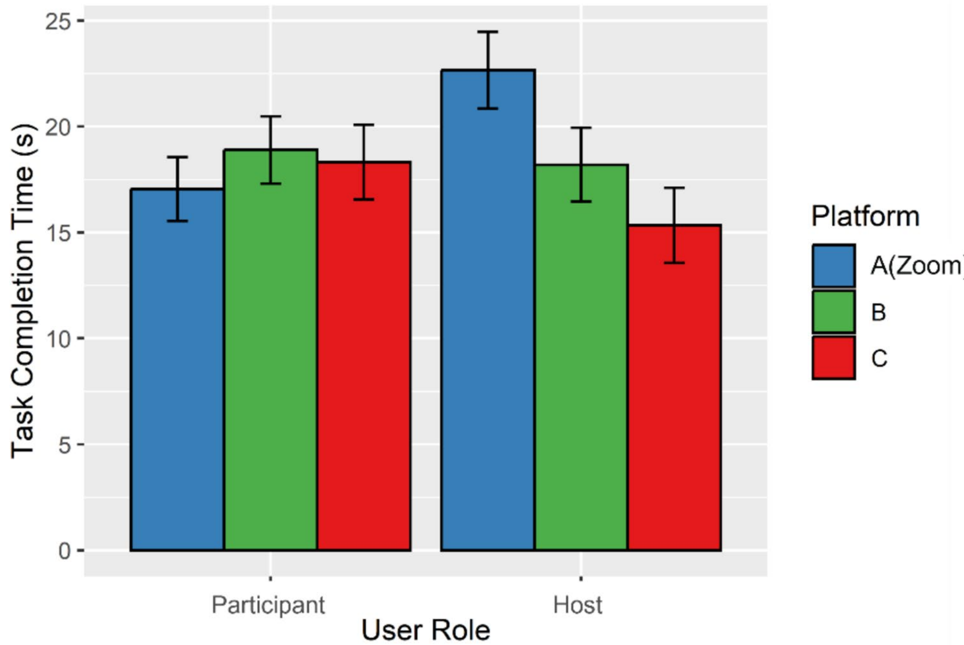

Fig. 6 Observed mean and standard error by user role

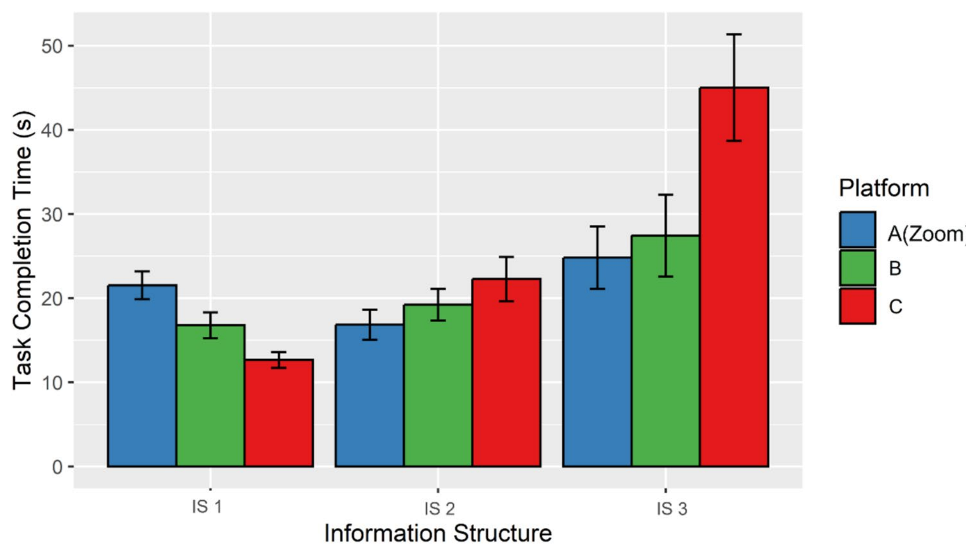

Fig. 7 Observed mean and standard error by information structure similarity

5 Discussion

The goal of this study was to examine whether transfer of training, i.e., improved performance on a new task due to prior interactions with a similar task, exists in older adults across different video conferencing platforms (VCPs). Older participants with previous experience in using the Zoom platform as meeting participants completed nine common tasks on Zoom as well as on two unfamiliar VCPs that share similarities with Zoom. Task performance was measured using task completion likelihood as well as task completion time (only for completed tasks). General linear models were developed, encompassing both mixed binary logistic regression and linear mixed models, and accounted for VCP, task similarity (categorized as either **User Role** or **Information Structure**), and their interactions as fixed effects predictors.

As expected, task similarity seems to have facilitated transfer of training to some extent. The **User Role** factor alone did not significantly influence task completion likelihood nor task completion time. Thus, the absence of worsened performance could suggest a positive transfer of training from *Participant* to *Host* tasks. However, some negative cases highlighted exceptions. Particularly, in *Platform C*, significantly decreased task completion likelihood for *Host* tasks was observed, indicating that transfer

Table 6 Parameter estimates of completion time (Platform + Task Flow)

	Task Completion Time (LMM)		
	Coefficient Estimate	(t-statistics)	*p*-value
Number of observations	359		
Fixed Effects			
Intercept	27.77	(6.133)	< 0.001**
Platform			
Platform A	(Reference)		
Platform B	− 3.43	(− 1.419)	0.157
Platform C	− 8.61	(− 3.562)	< 0.001**
Information Structure			
IS1	(Reference)		
IS2	− 0.86	(− 0.131)	0.899
IS3	29.59	(3.988)	0.005**
Platform: Information Structure			
Platform B: IS2	− 2.78	(− 0.750)	0.453
Platform C: IS2	17.80	(4.819)	< 0.001**
Platform B: IS3	− 1.26	(− 0.300)	0.764
Platform C: IS3	9.75	(2.329)	0.020*

$^{\cdot}p < 0.1$, $*p < 0.05$, $**p < 0.01$, $Conditional pseudo R^2 = 0.555$

of training was hindered for the unfamiliar *Host* tasks. On the other hand, the effects of task similarity on task performance were more clearly illustrated with respect to similarity in information structure. **Information Structure** alone had a significant effect on both task completion likelihood and task completion time. Specifically, a lower task completion likelihood and longer task completion times (for the completed cases) were observed when the information structure of a task was very different from its counterpart, i.e., Zoom, indicating the potential absence of transfer of training in these circumstances. But, in general, the effects of task similarity, in terms of both **User Role** and **Information Structure**, were highly dependent on specific platforms (discussed in more details in the following sections).

5.1 Platform and user role

With respect to the effects of task similarity in terms of **User Role**, the task completion likelihood for *Participant* tasks was similar across all platforms, but a significant decrease in task completion likelihood was observed for *Host* tasks in *Platform C,* which partially supported **Hypothesis H1** (Task completion likelihood is higher on *Participant* tasks than on *Host* tasks on unfamiliar platforms). This resulted in a significant interaction between **User Role** and **Platform**.

For *Participant* tasks, we expected to see a decrease in task completion likelihood between *Platforms A* and *B* compared to *Platform C* because of the difference in the location of information. However, this was not observed. Specifically, for *Participant* tasks, all relevant functions were first accessed from the menu bar, which was consistently positioned either at the top or bottom of the interface across all three VCPs (see panel ii of Figs. 1, 2, 3), while the remainder of the screen predominantly displayed other meeting participants or a shared screen. Thus, drawing from their prior interactions with participant tasks on Zoom (*Platform A*), older adult users could have been expecting to access most *Participant* task functions from a horizontal menu bar that generally displayed information in small rectangular area on the screen. One reason why task completion likelihood did not differ for *Participant* tasks was due to this similarity in display layout across the three VCPs, which could have enabled a positive transfer of training because the general structure of the information was the same. In other words, the similarity among display elements generally helped fulfill users' expectations, even though specific locations differed slightly.

However, for *Host* tasks, since participants did not have direct experience conducting these particular types of tasks on any of the VCPs, they first needed to search the menu options for each platform. In doing so, several differences across the platforms would have been noticed (more so than for *Participant* tasks). For example, the functions in *Platforms A* and *B* were housed within a menu bar located on the left side of the screen (as depicted in panel i of Figs. 1, 2), but were arranged at the top of the screen for *Host* tasks in *Platform C*. In addition, *Platform C* has many more menu options (see panel i of Fig. 3), some of which are unconventional, such as HUB and VIDEOS. Because of these types of differences, older participants likely needed to use more working memory, and experienced an increased cognitive workload, when processing these distinctive elements before deciding how to execute the task. In the case of *Platform C*, where the task completion likelihood decreased, the additional working memory load could have prevented a transfer of training, despite its layout similarity in terms of menu bar position with the baseline *Platform A + Participant* condition. This finding can be explained by the primitive information processing element (PRIM) model, where the use of working memory to copy an element received from a visual module from one place to another in a workspace is a deterministic factor of transfer task performance [15]. Thus, this phenomenon might have made it impossible for some users to complete the task requirements within the 60-s time allotment. It is also plausible that age-related changes in working memory [29] could have contributed to inhibited transfer effects for some participants. In addition, the menu task bar in *Platform C* did not have high contrast sensitivity with the background, potentially making it difficult for users to identify it as a menu bar. Research suggests that older adults tend to rely heavily on external cues to retrieve information from their memory when navigating new environments [10]. Thus, this lack of resemblance could have made the menu bar in *Platform C* seem foreign.

When considering only the completed tasks, similar to the analysis on task completion likelihood, task completion times for *Participant* tasks remained stable across platforms, suggesting that some amount of transfer of training occurred in cases where differences among layouts in *Participant* tasks across platforms were minimal. Surprisingly, the estimated task completion time for *Host* tasks was the longest in *Platform A* and shorter in *Platforms B* and *C*, which was unexpected based on **Hypothesis H3** (Task completion time is shorter on *Participant* tasks than on *Host* tasks on unfamiliar platforms).

The overall task completion rates were 70%, 79% and 56% for platforms A, B, and C, respectively. Thus, the negative impact of working memory associated with *Platform C* (as discussed previously) appears to have affected approximately 44% of users (who were unsuccessful), which is much higher compared to the other platforms. However, those who did complete the task were able to do so in less than 25 s (on average) across all conditions. The shorter task completion times for *Platforms B* and *C* may be explained by the fewer number of steps needed to execute *Host* tasks, especially in *Platform C*, compared to *Platform A* (see Hierarchical Task Analyses in Appendix 1), not by the extent of transfer of training. A previous study on transfer of training provide insights into this finding [17]. The authors explained that transfer of training reduced mostly the planning time, but barely execution time in their experiment. In our study, due to the limited transfer in *Platform C,* participants who failed to complete the tasks within 60 s likely spent more time planning and, thus, were excluded from task completion time analysis. In contrast, those who completed the task mostly spent their time on execution, meaning that their completion time could not have been affected by a transfer.

The shorter task completion times for *Host* tasks in *Platforms B* and *C* can also be attributed to the increase in task completion time in *Platform A*. Participants in this study had previous experience with *Platform A*, and could have been expecting to experience a similar user interface layout for *Host* tasks as in *Participant* tasks of *Platform A*. But this was not the case. *Host* tasks were not like *Participant* tasks, thus any advantages stemming from past experiences were likely minimized. Moreover, the attempt to recall and extrapolate existing procedures used for *Participant* tasks induced more complex cognitive processes [11]. This increased cognitive processing can result in imprecise anticipations of the subsequent actions necessary for task completion when the transfer task is not similar to the training task or a “false friend,” which could be worsened by the slowing of information processing speeds associated with aging [29]. However, participants did not have such expectations for *Platforms B* and *C*.

5.2 Platform and information structure

Compared to the **User Role**, the more significant effects of **Information Structure** better captured the adverse impacts that task (dis)similarity has on the transfer of training. Particularly, when older users encountered very different information structures across the three platforms as they navigated through menu options (*IS3*), the decreased task completion likelihood can be attributed mostly to **Information Structure** alone, and less to the platform-dependent **User Role** factor. This finding is supported by **Hypothesis H2** (Task completion likelihood is lower on tasks with information structures different from those in *Platform A (IS2 and IS3)* compared to tasks that are similar to those in *Platform A*). This outcome is consistent with previous literature [30] showing that older adults tend to use a knowledge-driven, top-down visual search strategy. Older adults’ reliance on existing mental models, in our case knowledge of *Platform A,* likely influenced how they searched the other interfaces. Thus, given the differences in information structures of tasks in the unfamiliar platforms, this strategy could have resulted in less search efficiency.

The mismatch between the realized information structure and deviation from an established mental model of menu navigation can lead to significantly longer task completion times and a lower likelihood of task completion within a limited timeframe. In our study, tasks H4 and P1 were categorized under *IS3*, indicating being very different in **Information Structure** compared to their counterparts in *Platform A*. In *Platform C*, these two tasks (H4: mute participants upon login; P1: un-mirror your video camera) required fewer steps because of a flattened menu structure (more details in Appendix 1). For instance, to access the 'mute participant' function, instead of navigating through 'meetings' and 'scheduling' as in *Platforms A* and *B*, users in *Platform C* have to start directly from a 'scheduling meeting' menu. While previous literature has recommended flatter menu structures for older users [31, 32], our results suggest that this method may not always be effective. A more compressed information structure that does not align with users' established mental models can cause confusion and negatively affect task performance. This delay can be exacerbated for older adults, who are often experience some difficulty in directing attention to surface-level information, such as navigation links and menus [33]. However, a more objective approach is needed to ascertain the extent of the mismatch between users' mental models and the systems' information structures.

For task completion time, the effects of **Information Structure** were more associated with **Platforms**. Similar to **User Role,** after the incomplete cases were excluded, differences in completion time were observed that were not necessarily the result of transfer of training, which is contrary to **Hypothesis H4** (Task completion time is shorter on tasks with information structures different from those in *Platform A* compared to tasks that are similar to those in *Platform A*). Specifically, when the information structures were very similar across all platforms (*IS1*), we found a significantly shorter task completion time for *Platform C*, potentially due to the reduced number of steps required to complete the tasks (as detailed in Appendix 1). However, as the information structure of *Platform C* became increasingly different in *IS2* and, especially, *IS3* conditions, the completion times were adversely impacted. Even when fewer steps were required for a task, such as with P1 and H4 tasks (classified as *IS3*) in *Platform C*, the negatively affected transfer of training outweighed the previously observed positive impact of reduced steps. Here, the "false friend" phenomenon also observed in *Host* tasks of *Platform A* could provide a reasonable explanation for this effect. Previous work has indicated that (mental) schema acquisition is one of the most important cognitive processes in the successful transfer of problem-solving skills [13], which allows users to recognize analogies between the training and the transfer tasks. Thus, we believe that the information structure similarity between the tasks facilitated such mapping, which had a positive impact on task performance.

5.3 Other potential influences on task performance

While this research suggests that task similarity is an important determinant of transfer of training [11, 16], the significant impact of **User Role** mainly occurred in interaction terms with **Platform**, illustrating that some variations in performance might have not been captured by our task similarity categorizations. Analysis from the post-experiment questionnaire revealed that 75% of participants felt that their knowledge of Zoom (*Platform A*) did not necessarily help them in navigating *Platform B*. Similarly, 80% of participants reported that their prior experiences with Zoom did not help them to navigate *Platform C*. This discrepancy between participants' self-perception of their own knowledge transfer and their actual performance potentially points to additional aspects of task similarity that are not effectively captured by neither the **User Role** nor **Information Structure** classification. Our participants explained that the naming of the VCP functions and differences in background colors between platforms made it difficult to navigate the new platforms and contributed, in part, to why they felt their prior experiences with Zoom did not benefit them. In addition, Livesey and Laszlo [16] highlighted that the particular task completion strategy employed by users can moderate the extent to which transfer of training exists for a given task. In our study, a few participants admitted to using at least three distinctive strategies to complete unfamiliar tasks. They included: (1) searching for setting options as the very first step, (2) looking for headers and icons that might were familiar to them, and (3) trying to recognize any commonalities across the platforms. This variation introduced by different task completion strategies can also contribute to task performance. While difficult to quantify, sensing techniques, i.e., eye tracking, can help provide additional objective data to determine the extent to which these strategies influence older users' task performance.

6 Summary

The findings from the study on the transfer of training in older adults using different video conferencing platforms (VCPs) provide several insights that align with existing literature on cognitive training and age-related task performance.

The results indicate that task similarity, particularly in terms of **User Role** and **Information Structure**, plays a significant role in the transfer of knowledge.

Overall, the consistent layout of **Participant** tasks across platforms likely facilitated familiarity and reduced cognitive load, thereby increasing task completion likelihood. Conversely, the challenges faced with **Host** tasks, particularly on *Platform C*, underscore the potential negative impacts that prior knowledge, shaped by existing mental models that are incompatible with newly encountered information structures, has on task performance. This finding further highlights the potential value of (when possible) maintaining consistent information structures for basic functions to support basic knowledge transfer.

Previous work has shown that older adults exhibit variability in their ability to transfer skills across different contexts, which can be influenced by their cognitive resources and prior experiences with similar tasks [34]. The mixed results observed for our task completion likelihood measure could also reflect the influence of individual differences among older adults, such as unaccounted for prior experience, cognitive flexibility, and interaction strategies.

7 Limitations and future work

Some limitations of this study should be acknowledged.

First, while the focus of this initial investigation was on older users, the engagement of older participants only may limit the generalizability of findings. Including younger and middle-aged participants in future work could enable more comprehensive evaluations of age-related differences and ability levels in the transfer of training.

Second, despite statistically significant results and good model fit parameters, a larger sample size could also promote greater generalizability of results. Given that recruitment was done using online crowdsourcing platforms during the COVID-19 pandemic with a convenient sample, we had limited control over the demographic and technological backgrounds of participants. Thus, older participants in this study may not fully represent the general aging population and its associated characteristics, and caution should be exercised in extrapolating these results to the broader older adult population. Future work should ensure more diversity among participants and conduct a larger scale study.

In this study, participants completed tasks based on their personal, unstructured experiences rather than undergoing standardized training or being assigned specific tasks beforehand. This lack of controlled prior experience may have led to varying levels of baseline knowledge and familiarity with the tasks, which could have impacted the results. When analyzing the effects of task similarity and prior knowledge, we considered how participants' pre-existing mental models of a particular VCP interface likely influenced their performance. In future research, estimating users' mental models using quantitative means would allow for a more precise delineation of how differences in task performance are linked to conflicts with established mental models.

Finally, task performance was evaluated based on a fully randomized task sequence. However, manipulating the task sequence more systematically would allow for better evaluation of the effects of both short- and long-term task experience on the performance metrics of interest, which can provide deeper insights into how variations in exposure times affect the transfer of training across different platforms and types of tasks.

8 Conclusion

This study adds to the literature on aging and technology, and offers valuable insights into transfer of training across various video conferencing platforms (VCPs) for older adult users. Overall, study results, related to task completion likelihood and times, suggest that there could be benefits to leveraging previous knowledge that users have gained from interactions with other similar systems. The current study elucidates that task similarity in terms of **Information Structure** could benefit older adults' task performance. Thus, maintaining consistency in the layout and arrangement of information, especially for core functions and fundamental features (such as changing audio output) across platforms, could help to exploit skill transferability. Additionally, this study highlights the potential detrimental impacts of increased cognitive overload, the "false friend" effect, and established mental models in knowledge transfer, emphasizing that past experiences might not always be advantageous, especially when transfer tasks bear limited resemblance to training tasks.

These preliminary insights offer designers of videoconferencing platforms potential ideas for enhancing usability, particularly for the growing aging population, who may rely on various VCPs to maintain social and professional connections. Although based on a limited and convenient sample, this work still provides useful empirical evidence that could be used to inform the design of other pervasive technologies, with the aim of supporting older adults in learning independently and building greater levels of technological self-efficacy.

Appendix 1: Task analysis

Hierarchical task analyses for all tasks

	Platform A	Platform B	Platform C
H1 (select a recorded meeting)	1. Open recording panel 1.1. Move mouse to the top left corner (AHmain) 1.2. Choose “recordings” 2. Choose Local Recordings 2.1. Move mouse to the top center of screen (AH6) 2.1. Choose “local recordings”	1. Open the recording panel 1.1. Move mouse to the top left corner (BHmain) 1.2. Choose “recording” 2. Choose the desired meeting (BH12)	1. Open the recording panel 1.1. Move mouse to the center top (CHmain) 1.2. Choose “recording” 1.3. Select the desired recorded meeting (CH9)
H2 (Select a past meeting)	1. Open meetings panel 1.1. Move mouse to the top left corner (AHmain) 1.2. Choose “meetings” 2. Choose “previous” 2.1. Move mouse to center top of screen (AH3) 2.2. Choose “previous” 3. Choose desired meeting	1. Open meetings panel 1.1. Move mouse to the top left corner (BHmain) 1.2. Choose “meetings” 2. Select completed meeting 2.1. Move mouse to the left of the top, center on screen (BH1) 2.2. Choose “completed” 2.3. Select desired past meeting (BH5)	1. Open the hub panel 1.1. Move mouse to the top center (CHmain) 1.2. Choose “hub” 1.3. Choose desired past meeting (CH1)
H3 (Schedule a meeting)	1. Open meetings panel 1.1. Move mouse to the top left corner (AHmain) 1.2. Choose “meetings” 2. Select “schedule a meeting” 2.1. Move mouse to the top right corner (AH1) 2.2. Choose “schedule a meeting” 2.3. Enter meeting details (AH2)	1. Open meetings panel 1.1. Move mouse to the top left of the screen (BHmain) 1.2. Choose “meetings” 2. Choose “scheduling” 2.1. Move mouse to the top right of the screen (BH1) 2.2. Choose “scheduling” 2.3. Enter meeting details on the new page (BH2)	1. Choose “schedule meeting” 1.1. Move mouse to the top left of the screen (CHmain) 1.2. Choose “schedule meeting 1.3. Enter meeting details (CH3)

	Platform A	Platform B	Platform C
H4 (automatically mute participants when they login)	1. Open meetings panel 1.1. Move mouse to the top left corner (AHmain) 1.2. choose "meetings" 2. Select "schedule a meeting" 2.1. Move mouse to the top right corner (AH1) 2.2. choose "schedule a meeting" 3. Select "mute participants upon entry" 3.1. Read all setting items (AH2) 3.2. Move mouse to the bottom center of the page (AH2) 3.3. Check "mute participants upon entry" box if empty	1. Open meetings panel 1.1. Move mouse to the top left of the screen (BHmain) 1.2. Choose "meetings" 2. Choose "scheduling" 2.1. Move mouse to the top right of the screen (BH1) 2.2. Choose "scheduling" 3. Choose "advanced options" 3.1. Read through the meeting details 3.2. Move mouse to the bottom of all the details (BH2) 3.3. Choose "show advanced options" 4. Choose audio connection options 4.1. Move mouse under advanced options (BH3) 4.2. Choose "audio connection options" 5. Choose mute when they join meeting 5.1. Move mouse under audio connection options (BH4) 5.2. Check "always mute attendees when they join the meeting" box if empty	1. Open meeting scheduling panel 1.1. Move mouse to top left corner (CHmain) 1.2. Click "schedule meeting" 2. Choose "advanced settings" 2.1. Read all settings items (CH3) Scroll down 2.2. Click "advanced options" (CH4) 3. Choose Mute upon entry" 3.1. Read all setting items (CH5.1) 3.2. Scroll down (CH5.2) 3.3. Check "advanced options" box if empty (CH5.3)
P1 (un-mirror your video camera)	1. Open the video setting 1.1. Move mouse to the bottom left of the screen (APmain) 1.2. Choose the "^" next to "start video" 1.3. Choose "video settings" (AP7) 2. Open "background & filters" 2.1. Move mouse to the middle of the left menu column (AP8) 2.2. Choose "background & filters" 3. Choose Un-mirror video 3.1. Move mouse to the bottom of the screen (AP8) 3.2. Un-check the "mirror my video" box if checked	1. Open video settings 1.1. Move mouse to the center bottom of screen (BPmain) 1.2. Choose the down arrow next to "start video" 2. Choose settings 2.1. move mouse slightly up from the bottom center of screen 2.2. "choose" settings (BP7) 3. Unmirror camera 3.1. Move mouse to the upper center of screen, to the top right of the preview window (BP8) 3.2. Choose the blue circle icon to un-mirror camera (BP9)	1. Open setting 1.1. Move mouse to the top right corner of screen (CPmain) 1.2. Choose "settings" 2. Choose general 2.1. Move mouse to toward the upper left of the new window in the middle of screen (CP7) 2.2. Choose "general" 2.3. Un-check the "mirror my self-view" box if checked (CP7)

	Platform A	Platform B	Platform C
P2(Replace your background with a virtual background)	1. Open the video setting 1.1. Move mouse to the bottom left of the screen (APmain) 1.2. Choose the "^" next to "start video" 1.3. Choose "video settings" (AP7) 2. Open "background & filters" 2.1. Move mouse to the middle of the left menu column (AP8) 2.2. Choose "background & filters" 2.3. Move mouse to the center of screen (AP8) Choose desired 2.4. virtual background	1. Choose settings 1.1. Move mouse to the bottom center of screen (BPmain) 1.2. Choose "v" next to "start video" 1.3. Choose "setting" (BP7) 2. Open "change virtual background" 2.1. Read through the menu 2.2. Move mouse to center of pop-up window 2.3. Choose "change virtual background" (BP9) 2.4. choose desired background (BP8)	1. open settings 1.1. move mouse to the top right corner (CPmain) 1.2. choose "settings" 2. choose "virtual background" 2.1. move mouse to the top center of the new pop-up page (CP6) 2.2. choose "virtual background" 2.3. select desired background
P3 (Switch the audio outlet from computer to phone)	1. Choose audio 1.1. Move mouse to the bottom left of screen (APmain) 1.2. Choose "^" next to "unmute" 2. Choose "switch to phone audio" 2.1. Move mouse to bottom left of screen (AP10) 2.2. Read pop out menu 2.3. Choose "switch to phone audio…"	1. Choose "…" 1.1. Move mouse to the bottom center of screen (BPmain) 1.2. Choose the vertical "…" 2. Choose switch audio 2.1. Move mouse toward the center of screen (BP10) 2.2. Choose "Switch audio"	1. Open settings 1.1. Move mouse to the top right corner of screen (CPmain) 1.2. Choose "settings" 2. Choose general 2.1. Move mouse to toward the upper left of the new window in the middle of screen (CP7) 2.2. Choose "general" 3. Choose audio through phone 3.1. Read through the menu 3.2. Under "audio": check the box "connect through phone" (CP7)
P4 (Send a message to all participants in the chat)	1. Choose chat 1.1. Move mouse to bottom center of screen (APmain) 1.2. Choose "chat" 2. Send message 2.1. Move mouse to the bottom right (AP2) 2.2. Click on text box "type message here…"	1. Choose chat 1.1. Move mouse to the bottom right of screen (BPmain) 1.2. Choose "chat" 2. Send message 2.1. Move mouse to bottom right of screen (BP2) 2.2. click on text box "enter chat message here"	1. Choose chat 1.1. Move mouse to the top right corner of screen (CPmain) 1.2. Choose "chat" 2. Send message 2.1. Move mouse to the bottom right of page (CP1) 2.2. Click on "type your message"
P5 (Share your screen)	1. Share screen 1.1. Move mouse to bottom center of screen (APmain) 1.2. Choose "share screen" 2. Choose screen 2.1. Move mouse to the top left of new window (AP5) 2.2. Choose "Desktop 1"	1. Share screen 1.1. Move mouse to the bottom center of screen (BPmain) 1.2. Choose "share" 2. Choose screen 2.1. Move mouse toward the center of screen (BP4) 2.2. Choose "Screen"	1. Choose apps 1.1. Move mouse to the top right corner of screen (CPmain) 1.2. Choose "apps" 2. Upload & share video 2.1. Move mouse to the middle right of the screen (CP14) 2.2. Choose "upload & share video"

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Declarations

Conflict of interest The authors declare no competing interests.

Ethical approval The study was approved by the Purdue University Institutional Review Board (Protocol: IRB-2020-1406) and was conducted according to the American Psychological Association (APA) Code of Ethics. All participants consented to participate in the study.

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