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Evaluation of Instructors' Demographic Variations on a Web-based Platform for Connecting with Practitioners

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ABSTRACT
Exploration of demographic variations is required to develop dynamic web platforms that cater to the varying preferences of diverse users. Hence, this study evaluated instructors' demographic variations on a web-based platform for connecting with practitioners for student development. Both objective and subjective measures were adopted to investigate age- and gender-related differences in gaze behavior, task completion time, perceived cognitive load, perceived usability, and trust. Compared to male instructors, female instructors had higher fixation counts, longer task completion times, and statistically significant longer fixation duration. Female instructors gave higher usability and trust ratings but reported a higher cognitive workload. Compared to Generation Y instructors, Generation X instructors had longer fixation duration, higher fixation count, and statistically longer task completion time. Generation X instructors reported high cognitive load, lower usability, and trust ratings. The study also reveals demographic differences in parameters that instructors focused on while connecting with practitioners via a web platform.

KEYWORDS
Age; demographic differences; gender; Generation X; Generation Y; instructors; web platform

1. Introduction

Preparing students for the construction industry in the current era of construction 4.0 requires more intimate interaction between practitioners and instructors (Zheng et al., 2019). Innovative means to achieve the required synergy remain a matter of question. However, the affordances of Web 2.0 for collaboration and interaction present an opportunity to foster connections between individuals and communities (Vlachopoulos & Makri, 2019). This has been leveraged through web platforms in several contexts such as connecting tutoring communities of practice (CoP) for tutoring activities (Garrot-Lavoué, 2011), connecting student–teachers with their CoP (Mackey & Evans, 2011), and biotechnology students with experts in the industry for mentoring (Khan & Gogos, 2013). Hence, web platforms could be used to facilitate intimate interaction between instructors and practitioners in preparing students for the workplace. To ensure usability and adoption by varying end-users, demographic considerations are important in the design of web platforms (Djamasbi et al., 2007; Romano Bergstrom et al., 2013). This could help develop dynamic web platforms that meet the diverse preferences and needs of different users (Djamasbi et al., 2010).

Prior studies (Djamasbi et al., 2007; Romano Bergstrom et al., 2013) have shown that gender and age account for differences in users' perception and usage of web platforms. For example, the information technology industry is male-dominated (Maudlin et al., 2020), hence lack of consideration for female audiences could lead to frustration and anxiety among female users, ultimately resulting in reduced satisfaction with web platforms (Lin & Hsieh, 2016). Moreover, inaccessible web platform interfaces with conventional "one-size-fits-all" designs affect the usage of web platforms by older adults (Machado et al., 2018; Romano Bergstrom et al., 2013). Also, gender- and age-related differences exist in online trusting behavior which affects the usage and perception of web platforms (Malik et al., 2016; Riedl et al., 2010). In addition, declination in cognitive processing and visual perception comes with age (Romano Bergstrom et al., 2013). Similarly, gender differences have been noted in the mental processing of information (Sargezeh et al., 2019). Hence, prior studies (Hewitt & He, 2022; Schmutz et al., 2010) have assessed perceived cognitive load in the evaluation of web platforms but without consideration for demographic variations. Studies (Chen et al., 2021; Yu, 2019) that have attempted to investigate demographic differences in cognitive load on web platforms have been in online learning among students. Majority of prior studies on demographic differences in web platform usage focused on e-commerce (Djamasbi et al., 2010; Hwang & Lee, 2018), news and entertainment (Buscher et al., 2009), and e-learning platforms (Rakoczi, 2017). Conversely, other studies (Papavlasopoulou et al., 2020; Rakoczi, 2017) have revealed that demographics have only a little effect on gaze behavior in web platform usage. Hence, demographic

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difference is still a matter of question, especially due to differences in the context of inquiry and demographics of users.

Web platforms could differ in various ways. These differences could be based on their purpose or function (e.g., e-learning, news, and entertainment) (Buscher et al., 2009; Rakoczi, 2017), visual stimuli (Pan et al., 2004), and end-user demographics (Machado et al., 2018; Romano Bergstrom et al., 2013). Hence, there is a need for the consideration of demographic variations in different contexts. For instance, Pan et al. (2004) and Djamasbi et al. (2010) showed that both users' demographics and visual stimuli of web platforms account for differences in users' gaze behavior. The visual stimuli include the interplay of textual, pictorial, and multimedia content as well as spatial, semantic, and visual characteristics which differ for web platforms (Pan et al., 2004). The interplay between visual stimuli and demographic differences has been reported in different contexts. For example, in e-commerce platforms (Djamasbi et al., 2010; Hwang & Lee, 2018), news and entertainment web platforms (Buscher et al., 2009), search engines (Buscher et al., 2009), and e-learning platforms (Rakoczi, 2017). The findings from these studies could help to enhance the usability of web platforms for different users (Djamasbi et al., 2007), yield valuable insights for both research and practical applications (Wang & Chen, 2012).

Therefore, this study assessed demographic variations (across age and gender) among instructors in a usability evaluation of a web platform designed to connect instructors with practitioners. The study uncovered demographic variations in gaze behavior, task completion time, perceived usability, perceived cognitive load, and trust among instructors in construction-related academic programs. This could be of interest to web developers and designers in the development of dynamic web platforms to meet the diverse needs and preferences of users, thereby enhancing usability, user experience, and adoption. Other sections of the article are organized as follows: the background section presents a literature review on demographic differences in the perception of web platforms. The methodology, results, discussion, and conclusion section follow this.

2. Background

2.1. Demographic differences in the perception of and interaction with web platforms

2.1.1. Gender

Gaze behavior on web platforms is influenced by gender (Djamasbi et al., 2007). With the aid of eye-tracking in a computer-based collage viewing activity among diverse participants (aged 10–60 years), Mohammad (2021) reported that females had shorter fixation duration than males. However, with participants of diverse jobs, backgrounds, education levels, and age range of 18–69, Buscher et al. (2009) reported that females had longer fixation durations and were more thorough while looking at web platforms compared to their male counterparts. The context of Buscher et al. (2009) was in information searching and page identification tasks using about 361 web pages. Among college students ranging in age from under 21 years to over 25 years, Hwang and Lee (2018) reported that women were drawn to more of the information displayed on a shopping web platform than men. However, men were highly influenced by visual attention to product information and consumer opinion, and they tended to trust online shopping information. In a similar context but with working adults (aged 18–34 years old), Tupikovskaja-Omovie and Tyler (2020) found that males and females had similar patterns of visual attention to product photos. However, Pan et al. (2004) using multiple web pages of different web platforms revealed that male college students exhibited longer fixation duration than female college students. Similarly, with college students aged 25–34 years, Sargezeh et al. (2019) reported that when compared to males, females had higher numbers of fixations and shorter fixation durations while looking at indoor pictures on a computer. Rakoczi (2017) argued that long fixation duration is an indication of higher cognitive load in understanding the meaning of graphical user interface (GUI) elements. However, longer fixation duration has been attributed to both males and females in existing studies. Gender differences in interaction with web platforms have been investigated in different scenarios using different types of participants, hence, this study focused on a different but specific context of instructor–practitioner collaboration via a web platform.

With older participants, Moss et al. (2006) showed that on web platforms, females favor the use of white, yellow, and pink while males have a visual preference for blue and black. Miller et al. (2020) showed no gender difference in the perceived usability of a web platform for symptom assessment and advice. However, among very diverse groups of participants, gender influences how the characteristics of a social commerce web platform affect perceived value (Molinillo et al., 2021). Among undergraduate and graduate students, Lin and Hsieh (2016) explored gender differences in website interface design criteria. The study reported that males prefer minimalist design and flexibility while females have preferences for learnability, consistency of design, and user support features. In the face recognition task, Sammaknejad et al. (2017) noted that in comparison with males, more exploratory eye behavior is noticeable among females hence, they tend to scan images faster. Malik et al. (2016) reported that men exhibited a higher level of trust in Facebook than women. Contrarily, Wendy (2015) reported that females are more likely to develop trust in an online environment than men. These existing studies are in various contexts, with different demographics of participants hence resulting in differing results. Therefore, there is a need to uncover gender differences in various types of web platforms with different demographics of users.

2.1.2. Age

Age is another demographic variable that influences users' behavior on web platforms. For example, as age increases, the number of fixations and saccades decreases (Dowiasch et al., 2015). Also, Meyer et al. (1997) reported that on a web platform, older people took longer to complete a task and frequently returned to the homepage. With participants' age range from 19 to 75, Romano Bergstrom et al. (2013) showed that on a web platform, older users fixated more on the middle of the screen, less frequently at the left side of the screen, frequently returned to the homepage, had lower accuracy and longer task completion time. The study also found that compared to younger users, older users fixated on the middle of the screen often but less frequently on the left side of the screen. Hence, the arrangement of navigational elements on the periphery rather than at the center of the screen could result in difficulties for older adults (Romano Bergstrom et al., 2013). Conversely, during information search tasks, Buscher et al. (2009) showed that younger participants looked significantly longer at the center region, but significantly shorter at the center-left position of the screen. Also, for recognition tasks, older participants looked significantly longer at the webpage and every region than younger participants. However, there are scarce studies that have used eye tracking to investigate age-related differences in the perception of web platforms (Hwang & Lee, 2018). Maramba et al. (2019) showed that questionnaires are one of the prominent tools used for the usability of web platforms. Idrees et al. (2023) opined that eye tracking is seldom used.

Huang and Benyoucef (2017) found that age influences how users perceive the social aspects, functionality, and usability of websites. Using a questionnaire, Miller et al. (2020) showed that younger patients (18–24 years old) perceived a web-based platform for symptom assessment and advice more helpful than older patients (70 years and above). With a usability questionnaire, van der Vaart et al. (2019) reported that as age increases, the perceived usability of a web-based cognitive behavioral therapy decreases. Mlikotic et al. (2016) revealed that younger women prefer the usage of a web platform for surveys than older women. However, with a structured questionnaire, Molinillo et al. (2021) showed that age does not influence users' behavior on web platforms in a social commerce context. Malik et al. (2016) and Sikun (2022) reported that younger users of social media platforms displayed higher trust than older ones. Conversely, Munar and Jacobsen (2013) reported similarities in how younger and older tourists trust social media. The only difference reported was that older tourists considered websites of destination management organizations and microblogging more trustworthy. Kumar and Lim (2008) assessed the age difference in mobile service perception between Generation Y and baby boomers. The study reported that the impact of emotional value on satisfaction is more pronounced among Generation Y individuals, whereas economic value plays a more significant role in satisfaction among baby boomers. However, studies comparing the perception of Generation X (those born between the early 1960s and early 1980s) and Generation Y (those born between the early 1980s and mid-1990s) in web platform usage seem scarce.

2.2. Theoretical underpinning

According to the cognitive load theory by Sweller (1994), information processing on web platforms can be influenced by the varying but limited cognitive resources possessed by individuals. Consideration of cognitive load is crucial because there is a tendency of cognitive overload while using web platforms which can lead to confusion and low satisfaction (Albers, 2011; Hu et al., 2017). This tendency is influenced by the amount of cognitive resources possessed by users which differs for different people (Albers, 2011). Hence, there is a need for the consideration of cognitive load in web platform usage to ensure minimal cognitive demand. In addition, consideration of demographic differences in the usage and perception of web platforms can be viewed from age and gender perspectives. Gender differences in visual perception, preferences, and information processing on web platforms have been reported in the literature (Djamasbi et al., 2007; Hwang & Lee, 2018). Djamasbi et al. (2007) opined that these differences are due to inherent attributes. Selectivity theory clarifies these differences by explaining that males and females process information with different parts of the brain, hence, the differences (Meyers-Levy & Loken, 2015). The concept of digital natives and digital immigrants by Prensky (2001) explained age-related differences in the perception of information technology. Prensky (2001) explained that digital natives are those of the younger generation (such as Generations Y and Z) who grew up with information technology while digital immigrants (such as baby boomers and Generation X) are older adults who had to learn to use information technology. This generational divide has been used to explore individual differences in domains such as the usage of mobile networks (Kumar & Lim, 2008) and digital learning among students (Creighton, 2018) but with limited application in web platform usage (Djamasbi et al., 2010). Therefore, given the position of literature as stated above, this study aimed to uncover demographic variations about age and gender in the evaluation of a web platform by instructors in construction-related academic programs.

3. Methodology

3.1. Overview of the methodology

The web platform used in this study is called ConPEC designed to connect instructors in construction-related academic programs and practitioners for collaborations aimed at students' development. The platform was designed after inputs from the potential end-users were sourced via surveys and focus group sessions (Yusuf et al., 2024). After registration on the web platform (this involves signing up, logging in, and profile completion), three critical tasks must be performed by instructors to be connected with a practitioner who can meet their course-support needs. These tasks include inputting details of the course-support request (i.e., class size, student academic level and program of study, date, and time when the course support is needed), defining preferences regarding preferred/suitable practitioners (i.e., area of expertise, years of experience, and level of education) followed by submission of the request and finally, selection of preferred/suitable practitioner from the recommended list. The participants interacted with several web pages on the web platform. The web platform can provide recommendations of suitable practitioners to instructors based on the request submitted. Therefore, the participants viewed the details of recommended practitioners one after the other before making a selection. The webpages that correspond to the third critical task where instructors view details of recommended practitioners and make a selection were chosen as the focus for the eye tracking. This is because the webpage contained the details of practitioners identified from the survey and focus group which instructors would consider while seeking practitioners who could meet their course-support needs (Yusuf et al., 2024). A sample of the webpage showing one practitioner's details (out of other recommendations) which represent the areas of interest (AOIs) is shown in Figure 1. The instructors who participated in this study examined many of the sample webpages (Figure 1) showing details of a recommended practitioner to decide whether they would select the practitioner to provide support in their classes. All the participants followed the usage of the web platform as described above. None of the participants had prior exposure to the web platform.

3.2. Experimental procedure and data collection

All the participants followed the experimental procedure as explained to them after signing the informed consent form as approved by the Virginia Tech Institutional Review Board (IRB 23-046). The study employed a screen-based eye-tracker called Tobii Pro Nano (with a sampling frequency of 60 Hz) connected via a USB 2.0 port to a computer (1920 pixels by 1080 pixels resolution) on which the participants interacted with the web platform. The precision and accuracy of Tobii Pro Nano are 0.10° and 0.3° root mean square, respectively. The eye tracker uses infrared illuminators via image sensors to generate reflection patterns on the corneas of the participant's eyes. The reflection patterns and the eyes are identified using advanced image processing algorithms (Tobii, 2023). The device employs a single-camera system that combines dark and bright pupil tracking, using advanced mathematical techniques to compute the three-dimensional coordinates of each eye, and consequently the gaze points (Tobii, 2023). The eye tracker was used to collect eye-tracking data for the entire session as participants interacted with the web platform on a personal computer. Before data collection, the eyes of the participants were calibrated, and they all had at least 75% gaze samples similar to Chen et al. (2019). Fixation count and fixation duration were used to assess demographic variation in visual perception and interaction with the web platform similar to prior studies (Papavlasopoulou et al., 2020; Sargezeh et al., 2019). The experiment involves the usage of the web platform in a real case scenario as described in Section 3.1. Each session of the experiment was performed under identical conditions. After interacting with the web platform, participants completed the National Aeronautics and Space Administration Task Load Index (NASA TLX), demographic, system usability scale (SUS), and Trust questionnaires. The SUS questionnaire is on a five-point Likert scale (1 – strongly disagree, 5 – strongly agree) while the Trust questionnaire is on a seven-point Likert scale (1 – not at all, and 7 – extremely). Only the mental demand, frustration, and effort dimensions of the NASA TLX were considered in this study. NASA TLX was adopted to measure perceived cognitive load (Hewitt & He, 2022), the SUS questionnaire was used to assess perceived usability (Idrees et al., 2023), and the trust questionnaire (Jian et al., 2000) was used to assess users' level of trust in the web platform. Minor modifications were made to the original scales. For the SUS and trust questionnaires, only the word "system" in the original scales was replaced with "platform". Prior studies (Bangor et al., 2008; Pal & Vanijja, 2020) have done similar modifications without impacting the validity of the data collection instrument. To ensure the content and face validity of the data collection instruments, an external evaluator with extensive experience

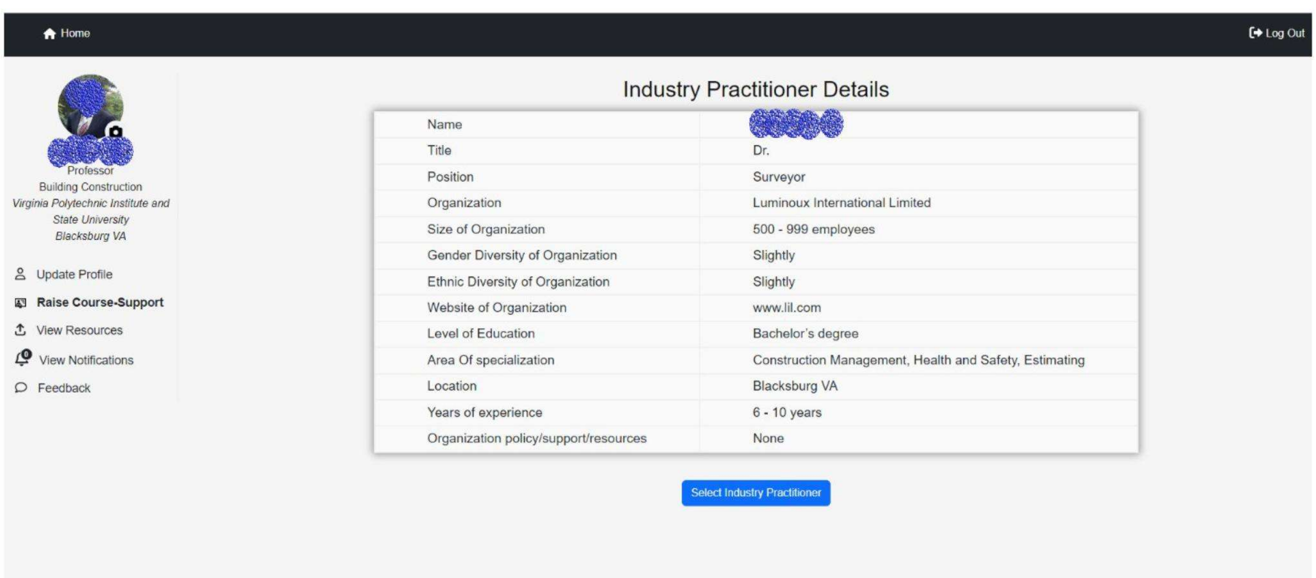

Figure 1. Areas of interests (practitioner's details that instructors would consider). *Source*: Created by authors.

also evaluated the data collection instruments. No modification was made to the original NASA TLX. These data collection instruments have adequate psychometric properties and have been used in prior studies (Jian et al., 2000; Pal & Vanijja, 2020; Sharek, 2011). To ensure the anonymity of the participants, they were each assigned a random number based on the time they participated in the experiment. Also, access to participants' demographic data was strictly controlled by storing it on a password-protected computer, and only members of the research team were granted access. In addition, during data analysis, the data were de-identified and participants' personal identifiable information was removed or replaced with unique identifiers to ensure anonymity and preserve the usefulness of the data for analysis. The data anonymization procedures were reviewed and approved by the Virginia Tech Institutional Review Board to ensure compliance with privacy regulations and ethical standards. The experiment session took an average of 1 hour 25 minutes per participant. An overview of the experiment procedure is shown in Figure 2.

3.3. Participants

The participants include 20 instructors (faculty members) in construction-related academic programs at Virginia Tech. Participants who were 40 years old and younger were classified as Generation Y (born between the early 1960s and early 1980s). In comparison, those who were 41 years old and older were classified as Generation Y (Born between the early 1980s and mid-1990s) according to the classification by Glazer et al. (2018). No participants fall into Generation Z or baby boomers categories. Prior studies (Buscher et al., 2009; Idrees et al., 2023; Oyekunle et al., 2020) have used similar sample sizes. Ten of the participants were Generation X and 10 were Generation Y. Nine of the participants were male while 11 were female. No participant was identified as non-binary.

3.4. Data analysis

The fixation count and fixation duration of each participant on the AOIs were extracted in Tobii Pro Lab software and exported to Microsoft (MS) Excel (Redmond, WA). Only the eye tracking data for the duration, when the participants viewed details of all recommended practitioners and finally made a selection, was considered. Mean score and Wilcoxon's rank sum tests were used for the data analysis using MS Excel (Redmond, WA) and Statistical Package for the Social Sciences (v.20) (SPSS Inc., Chicago, IL). The Shapiro–Wilk (SPW) test showed that most of the dataset were not normally distributed (SPW values were <0.05). Therefore, the Wilcoxon rank sum test, a non-parametric test that does not assume the normality of the data set (Haynes, 2013; Nahm, 2016) was adopted to compare different demographic categories. The Wilcoxon rank sum test is also considered suitable for ordinal and continuous variables (Nahm, 2016; Natarajan et al., 2012). Cronbach's Alpha values of 0.69, 0.81, and 0.86 for NASA TLX, SUS, and Trust questionnaires respectively underscored the internal consistency of the data collection instrument (Taber, 2018).

4. Results

4.1. Gender-related differences

4.1.1. Fixation count

As shown in Figure 3, female instructors had a higher fixation count on all the AOIs except one which is "size of the organization". Overall, the female instructors had a higher fixation count on the AOIs. However, no statistically significant difference was observed ($p > 0.05$).

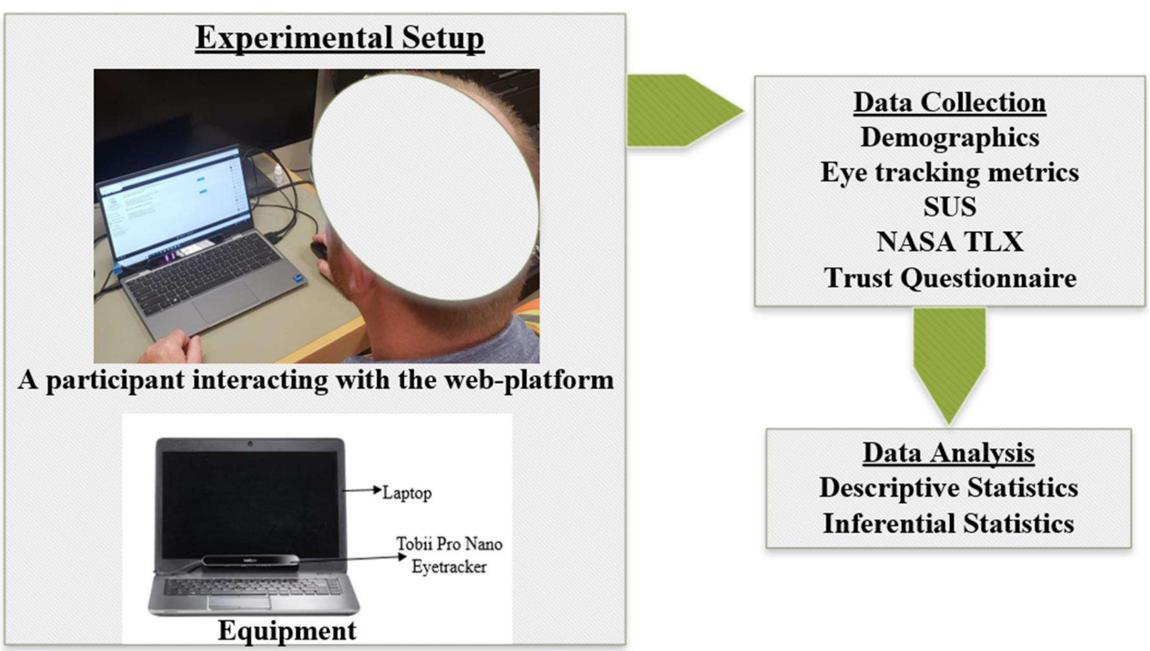

Figure 2. Overview of experiment procedure. *Source*: Created by authors.

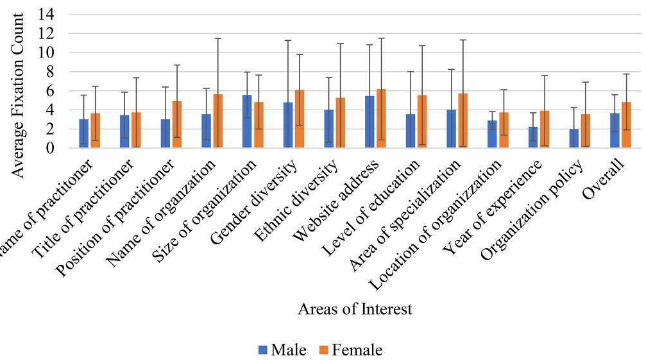

Figure 3. Comparison of average fixation count between male and female instructors. *Source*: Created by authors.

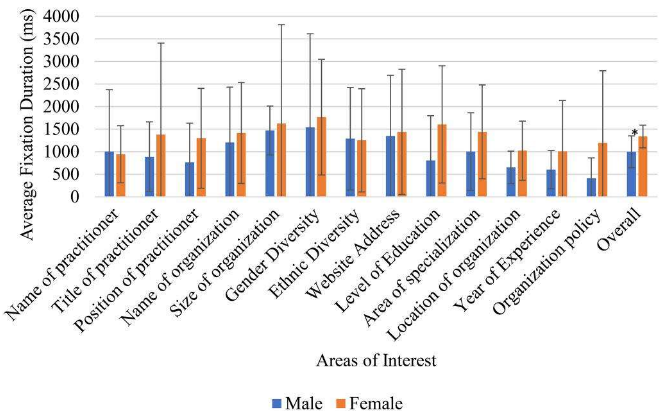

Figure 4. Comparison of average fixation duration between male and female instructors. *Significant at p value <0.05. *Source*: Created by authors.

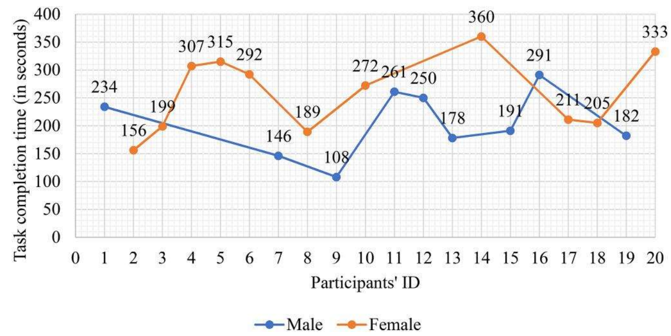

Figure 5. Comparison of task completion time between male and female instructors. *Source*: Created by authors.

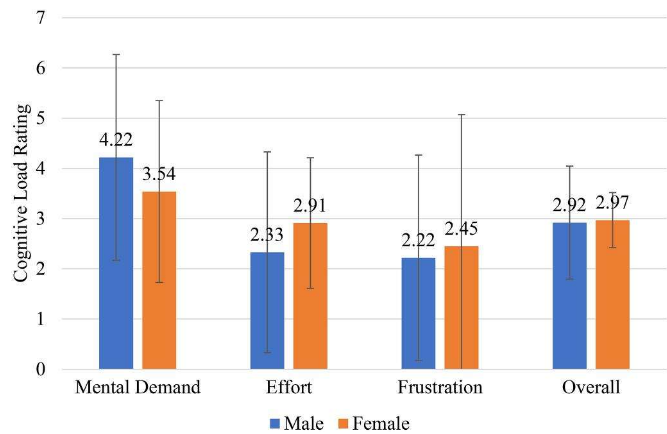

Figure 6. Comparison of perceived cognitive load between male and female instructors. *Source*: Created by authors.

4.1.2. Fixation duration

Figure 4 shows that female instructors had higher average fixation duration on most of the AOIs although no statistically significant difference was observed ($p > 0.05$). The male instructors had a higher average fixation only on two AOIs which are "Name of practitioners" and "Ethnic Diversity". Overall, the female instructors had statistically higher average fixation duration ($p < 0.05$) on the AOIs than the male instructors.

4.1.3. Task completion time

The average task completion time of the three critical tasks for male instructors was 205 seconds (about three and a half minutes) while that of female instructors was 258 seconds (about four and a half minutes). Female instructors took longer time to complete the tasks. This is further shown in Figure 5. Wilcoxon's rank sum test shows that there is no statistically significant difference ($p > 0.05$) between the task completion time of male and female instructors.

4.1.4. Perceived cognitive load

The results in Figure 6 show that male instructors reported higher mental demand in using the web platform. However, the female instructors reported higher effort and frustration. Also, overall, the female instructors reported a higher perceived cognitive workload than the male instructors. No statistically significant difference was observed ($p > 0.05$) between the two categories of participants.

4.1.5. Perceived usability

As shown in Table 1, the Wilcoxon rank sum test showed no statistically significant difference ($p > 0.05$) in the SUS rating of male and female instructors. However, the average SUS score (88.06%) by male instructors was lower than the average SUS score (89.77%) by female instructors. Also, female instructors gave higher ratings to most of the positive statements and lower ratings to all the negative statements compared to their male counterparts (see Table 1). The overall mean scores for the positive statements were 4.31 and 4.36 for male and female instructors, respectively. The overall mean scores for the negative statements were 1.27 and 1.18 for male and female instructors, respectively.

4.1.6. Trust

No statistically significant differences were observed in the mean score rating by male and female instructors ($p > 0.05$) (see Table 2). However, female instructors gave higher trust ratings to most of the positive statements and higher ratings to all the negative statements compared with male instructors. The overall mean scores for the positive statements were 5.44 and 5.53 for male and female instructors, respectively. The overall mean scores for the negative statements

Table 1. Comparison of SUS ratings for male and female instructors.

S/N	Statements	Overall	Gender M	Gender F	*p* Value
	Positive statements				
1	I thought the platform was easy to use	4.80	4.78	4.82	0.882
2	I would imagine that most people would learn to use this platform very quickly	4.70	4.67	4.73	0.941
3	I felt very confident using the platform	4.55	4.44	4.64	0.656
4	I found the various functions in this platform were well integrated	3.95	4.11	3.82	0.710
5	I think that I would like to use this platform frequently	3.70	3.56	3.82	0.456
	Negative statements				
6	I thought there was too much inconsistency in this platform	1.35	1.44	1.27	0.603
7	I needed to learn a lot of things before I could get going with this platform	1.25	1.33	1.18	0.882
8	I found the platform unnecessarily complex	1.20	1.22	1.18	0.882
9	I found the platform very cumbersome to use	1.20	1.22	1.18	0.882
10	I think that I would need the support of a technical person to be able to use this platform	1.10	1.11	1.09	0.941

M: male; F: female.

Table 2. Comparison of male and female trust ratings.

S/N	Statements	Overall	Gender M	Gender F	*p* Value
	Positive statements				
1	I am familiar with the platform	5.95	5.89	6.00	0.882
2	I am confident in the platform	5.80	5.78	5.82	0.941
3	I can trust the platform	5.70	5.56	5.82	0.503
4	The platform has integrity	5.65	5.56	5.73	0.882
5	The platform is reliable	5.40	5.33	5.45	0.882
6	The platform is dependable	5.30	5.00	5.55	0.456
7	The platform provides security	4.65	5.00	4.36	0.603
	Negative statements				
8	I am wary of the platform	1.60	1.33	1.82	1.000
9	I am suspicious of the platform's intent, action, or outputs	1.45	1.22	1.64	0.941
10	The platform is deceptive	1.25	1.22	1.27	0.710
11	The platform behaves in an underhanded manner	1.25	1.22	1.27	0.710
12	The platform will have harmful or injurious outcome	1.10	1.00	1.18	0.766

M: male; F: female.

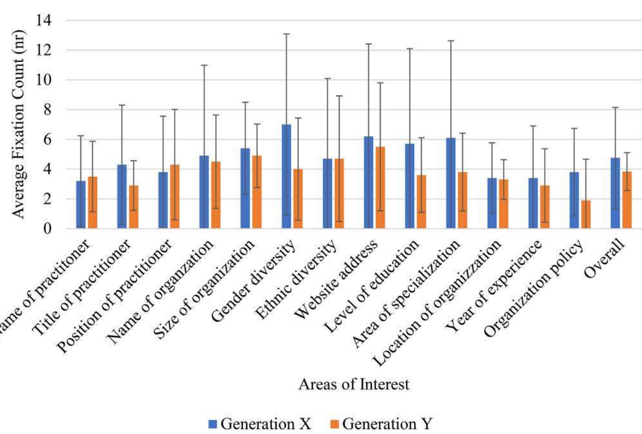

Figure 7. Comparison of average fixation count between Generation X and Y instructors. *Source*: Created by authors.

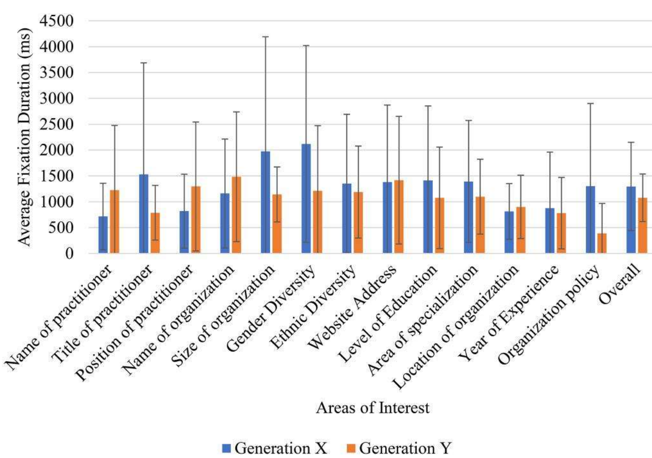

Figure 8. Comparison of average fixation duration between Generation X and Y instructors. *Source*: Created by authors.

were 1.20 and 1.44 for male and female instructors, respectively.

4.2. Age-related differences

4.2.1. Fixation count

Figure 7 shows the average fixation count on the AOIs for both Generation X and Y instructors. Generation X instructors had a higher fixation count on most of the AOIs compared with Generation Y instructors. The study shows that Generation Y instructors had a higher fixation count on three AOIs (i.e., name of practitioner, position of practitioner, and ethnic diversity of the practitioner's organization). The overall fixation count shows that instructors in Generation X had a higher average fixation count in all the AOIs compared to their counterparts. However, no statistically significant difference was observed ($p > 0.05$).

4.2.2. Fixation duration

Figure 8 shows the average fixation duration on the AOIs for both Generation X and Y instructors. No statistically

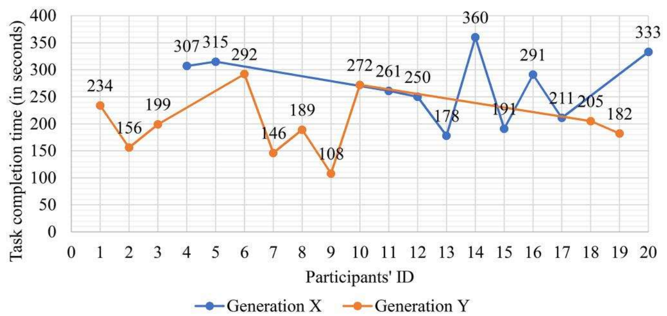

Figure 9. Comparison of task completion time between Generation X and Y instructors. *Source*: Created by authors.

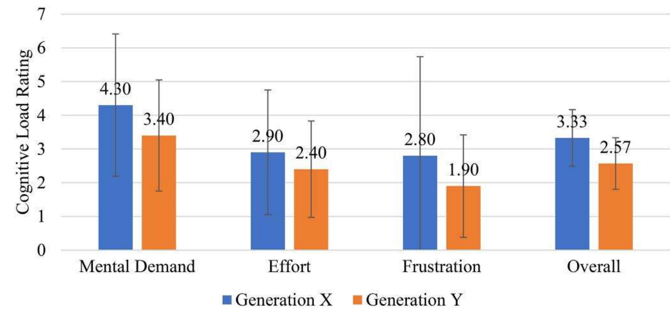

Figure 10. Comparison of perceived cognitive load between Generation X and Y instructors. *Source*: Created by authors.

significant difference was observed ($p > 0.05$). However, overall, Generation X participants had higher average fixation duration on the AOIs. Also, out of the 13 AOIs, the same participants had higher fixation duration on eight AOIs. These include the title of the practitioner, size of the organization, level of education, area of specialization, years of experience, organization policy, gender diversity, and ethnic diversity of the practitioner's organization.

4.2.3. Task completion time

The average task completion time for Generation X instructors to complete the three critical tasks was 270 seconds (about four and a half minutes) while that of Generation Y instructors was 198 seconds (about three and a half minutes). As further shown in Figure 9, most of the Generation Y instructors completed the task in a shorter time compared to their counterparts. Wilcoxon's rank sum test shows a statistically significant difference ($p < 0.05$) between the task completion time of Generation X and Generation Y instructors.

4.2.4. Perceived cognitive load

Figure 10 shows that Generation X instructors reported higher mental demands, effort, and frustration than Generation Y instructors. Overall, Generation X instructors reported a higher perceived cognitive load. However, no statistically significant difference ($p > 0.05$) was observed between the two groups of instructors.

4.2.5. Perceived usability

Table 3 reveals that Generation Y instructors gave higher perceived usability ratings to most of the positive statements as well as lower ratings to most of the negative statements. Generation Y instructors had an average SUS score (90.25%) that is greater than that of Generation X instructors (87.75%), though there was no statistically significant difference ($p > 0.05$). The overall mean scores for the positive statements were 4.28 and 4.40 for Generation X and Y instructors, respectively. The overall mean scores for the negative statements were 1.26 and 1.18 for Generation X and Y instructors, respectively.

4.2.6. Trust

As shown in Table 4, the Generation Y instructors gave higher trusting ratings to most of the positive statements and lower ratings to most of the negative statements. No statistically significant differences were observed in the mean score ranking by Generation X and Generation Y instructors ($p > 0.05$). The overall mean scores for the positive statements were 5.34 and 5.64 for Generation X and Y instructors, respectively. The overall mean scores for the negative statements were 1.44 and 1.22 for Generation X and Y instructors, respectively.

5. Discussion

Although the participants were somewhat homogenous (similar work domain (i.e., construction-related academic programs), expertise, and experience), demographic variations in their perception of web platforms were uncovered. This bears credence to Riedl et al. (2010) who noted that beyond other variables, biological factors (such as gender and age) are major factors influencing human behavior in web platform usage and perception.

5.1. Gender-related differences

The higher fixation counts and longer fixation duration by the female instructors align with Buscher et al. (2009). However, this finding is at variance with that of Papavlasopoulou et al. (2020) and Sargezeh et al. (2019). The differences in the findings could be due to differences in the context and age of the participants in the studies. For example, the participants in Papavlasopoulou et al. (2020) were K-12 students (aged 8–17 years old) in coding activities while the participants in this study were older. Specifically, the female instructors had less fixation count on the size of the practitioner's organization. Hence, they were less concerned if a practitioner works for a small, medium, or large construction firm. Also, female instructors had lower fixation duration on the name of the practitioner and ethnic diversity of the practitioner's organization. Unlike the female instructors, the male instructors were more concerned about these details while connecting with practitioners. Previous studies (Mahdy, 2018; Sijapati, 2023) have shown that women are less discriminatory. However, the longer fixation duration and higher fixation count on more AOIs by the

Table 3. Comparison of SUS rating of Generations X and Y.

S/N	Statements	Overall	Generation X	Generation Y	*p* Value
	Positive statements				
1	I thought the platform was easy to use	4.80	4.80	4.80	0.781
2	I would imagine that most people would learn to use this platform very quickly	4.70	4.60	4.80	0.503
3	I felt very confident using the platform	4.55	4.40	4.70	0.313
4	I found the various functions in this platform were well integrated	3.95	3.90	4.00	0.664
5	I think that I would like to use this platform frequently	3.70	3.70	3.70	0.503
	Negative statements				
6	I thought there was too much inconsistency in this platform	1.35	1.30	1.40	0.626
7	I needed to learn a lot of things before I could get going with this platform	1.25	1.40	1.10	0.549
8	I found the platform unnecessarily complex	1.20	1.30	1.10	1.000
9	I found the platform very cumbersome to use	1.20	1.20	1.20	0.654
10	I think that I would need the support of a technical person to be able to use this platform	1.10	1.10	1.10	1.000

Table 4. Comparison of Generation X and Y trust ratings.

S/N	Statement	Overall	Generation X	Generation Y	*p* Value
	Positive statements				
1	I am familiar with the platform	5.95	5.60	6.30	0.123
2	I am confident in the platform	5.80	5.80	5.80	1.000
3	I can trust the platform	5.70	5.50	5.90	0.247
4	The platform has integrity	5.65	5.60	5.70	1.000
5	The platform is reliable	5.40	5.20	5.60	0.579
6	The platform is dependable	5.30	5.20	5.40	0.853
7	The platform provides security	4.65	4.50	4.80	0.684
	Negative statements				
8	I am wary of the platform	1.60	1.90	1.30	0.481
9	I am suspicious of the platform's intent, action, or outputs	1.45	1.80	1.10	0.436
10	The platform is deceptive	1.25	1.10	1.40	0.684
11	The platform behaves in an underhanded manner	1.25	1.20	1.30	0.796
12	The platform will have harmful or injurious outcome	1.10	1.20	1.00	0.739

female instructors reveal that, overall, they are more concerned and thorough about the details of practitioners whom they collaborate with. This could be because as shown by Tartari and Salter (2015), compared with their male counterparts, female instructors in male-dominated disciplines (such as construction and engineering) often experience marginalization, have less social capital, and collaborate less with the industry. This experience of female instructors could have influenced their gaze behavior on the web platform for collaborating with practitioners. The male instructors had shorter task completion times than the female instructors. The longer task completion time of the female instructors could be because, as shown by previous studies (Hess et al., 2005; Hwang & Lee, 2018) females tend to pay attention to more information on web platforms than males. This also underscores the exploratory eye behavior of females and their tendency to be more thorough while using web platforms (Buscher et al., 2009; Sammaknejad et al., 2017). This also agrees with the selectivity theory which revealed that in information processing, females engaged in thorough analysis of information with the left hemisphere of the brain which is comprehensive. While males use the right hemisphere is very selective, focusing on easily noticeable content (Goodrich, 2014; Meyers-Levy & Loken, 2015). These characteristics of females could have led to their longer task completion time.

A higher cognitive load was reported by the female instructors. This agrees with Chen et al., (2021), and Yu (2019) who showed that females (although students) had a higher cognitive load in learning with a screen-based intelligent robot, and mobile learning environment, respectively. It is noteworthy that female instructors had higher fixation duration and higher cognitive load. This supports previous research (Rakoczi, 2017) that has shown that longer fixation is synonymous with higher cognitive load. As argued by Rakoczi (2017), the high cognitive load by female instructors could be due to their longer fixation duration because it is an indicator of high cognitive load resulting from understanding GUI elements. Also, the higher cognitive load could probably be because female instructors typically collaborate less with the industry as shown by Tartari and Salter (2015). Additionally, this could also be because the web platform used in this study was developed by men. This is vital as shown by Maudlin et al. (2020) that the information technology industry is male-dominated, and web platforms designed without consideration for female audiences could lead to frustration and anxiety among female users. Previous studies (Djamasbi et al., 2007; Moss et al., 2006) have shown that females prefer products designed by fellow females, and they also differ from men in color preference. Also, the prominent colors in the web platform used in this study were blue, black, and white. However, Moss et al. (2006) showed that males prefer blue and black while females prefer white, yellow, and pink on web platforms. Hence, the colors that females preferred were not prominent on the web platform. This could have contributed to the higher self-reported cognitive load by female participants because it could have led to frustration and anxiety for them

(Maudlin et al., 2020). Therefore, the use of colors preferred by both genders could be achieved using adaptive and personalized interfaces. Also, inputs from female web designers and female end-users could help to ensure that female preferences are captured in the design of specific web platforms.

Despite the higher self-reported cognitive load by the female instructors, the female instructors still gave a higher usability rating of the website. This shows that their perceived cognitive load did not affect their perceived usability of the web platform. This could be because, compared to male instructors, female instructors could have perceived the web platform as more useful in connecting with practitioners due to their lesser social capital which affects their collaboration with practitioners (Tartari & Salter, 2015). In addition, despite that the web platform was developed by men without colors that females have been shown to prefer, female participants still gave higher usability ratings. However, this result differs from Cyr and Bonanni (2005) who showed that women are consistently less pleased with a web platform than men. Also, despite the higher self-reported cognitive load, the female instructors gave a higher trust rating to the web platform. This shows that their perceived cognitive load did not impact their perception of usability and how trustworthy the web platform was. This result agrees with Wendy (2015) who noted that females are more likely to develop trust in an online environment. The finding, however, disagrees with other studies such as Malik et al. (2016) and Garbarino and Strahilevitz (2004) that have reported otherwise. This could be because these prior studies used more heterogeneous participants while the participants in this study are somewhat homogenous being in the same work domain with similar knowledge, skill, and expertise. Also, prior studies were in other contexts such as social media (Malik et al., 2016) and e-commerce (Garbarino & Strahilevitz, 2004) with more heterogeneous participants.

5.2. Age-related differences

Generation X instructors had both longer fixation duration and higher fixation count than Generation Y instructors. This finding agrees with Dowiasch et al. (2015) who opined that number of fixations increases with age. The results also agree with Buscher et al. (2009) who reported that older participants fixate longer on a web page than younger participants. This could be because the reduction in vision perception comes with age (Romano Bergstrom et al., 2013) which could have led to higher fixation count and longer fixation duration for the Generation X instructors while trying to understand the content of the web platform. The longer fixation duration and higher fixation count by Generator X instructors could be because they were more concerned about the details of the practitioners they collaborated with. Their prior experience might be responsible for this. As opined by Günther (2007), this could also be because people belonging to Generation Y, are less likely to read all the content on a web page, hence they would spend less time fixating. It is worthy of note that Generation Y instructors had both higher fixation count and longer duration on the name and position of practitioners. In addition, they had longer fixations on the name, website address, and location of the practitioner's organization. Hence, this reveals that these parameters are of higher consideration for Generation Y instructors while collaborating with practitioners. Generation X instructors took longer to complete the task. Despite that all the participants had similar levels of education, experience, and expertise, age still influenced the task completion time and gaze behavior. Generation X instructors reported higher cognitive demand. This could be due to the decline in cognitive processing that comes with age (Romano Bergstrom et al., 2013). The longer fixation duration by the participants could also be because Generation X participants had difficulties understanding the GUI elements. This could be the case because as noted by Rakoczi (2017), long fixation duration is an indication of high cognitive load. Another probable reason for this could be because the designers of the web platform used for the study are Generation Y. Hence, the web platform might not have been designed with consideration for older users which could have influenced their perceived cognitive load. This supports prior studies (Idrees et al., 2023; Romano Bergstrom et al., 2013) that have advocated for the consideration of older users' preferences while designing web platforms.

Also, Generation X instructors had lower perceived usability of the web platform. This could have been because the difficulty in exploring the GUI elements as shown by the longer fixation duration and high cognitive load influence their perceived usability of the web platform. The findings agree with van der Vaart et al. (2019) who noted that as age increases perceived usability decreases. The lower perceived usability of the web platform by Generation X instructors could be because the web platform used in this study was developed by Generation Y personnel. Hence, they could have developed the web platform without specific consideration for Generation X users. Therefore, the design of user interfaces as well as users' perceptions could be enhanced with adequate regard to their differing preferences. Generation X gave lower trust ratings compared to Generation Y. The higher self-reported cognitive load as well as the lower perceived usability rating could have influenced their perception of how trustworthy the web platform was. Prior studies (Christine Roy et al., 2001; Samson & Kostyszyn, 2015) have shown that high cognitive load and low usability could lead to less trust. Also, this could be because Generation Y is more computer savvy and more open to technology usage. After all, they grew up with technology while Generation X had to learn it. This could have affected their perception of the web platform regarding trust. This finding is parallel to previous studies (Malik et al., 2016; Sikun, 2022) that have reported similar findings.

The findings of this study revealed that different categories of web platform users have different perceptions and preferences. The findings showed the need for improvement on the web platform to reduce cognitive load for female and Generation X instructors, as well as increase male and Generation X instructors' perceived trust and perceived usability. The understanding of demographic variations in web platforms uncovered in this study could provide designers and developers with a robust perspective to ensure that the needs and preferences of different user types are considered. Most web platforms are used by heterogeneous users with different demographics accompanied by diverse needs and preferences. This is further heightened by the increasing diversity of web platform users (Mazuera et al., 2007). These demographic differences vary widely and could most of the time be conflicting. For example, Moss et al. (2006) showed that females prefer white, yellow, and pink colors on webpages while males prefer blue and black. Also, Romano Bergstrom et al., (2013) showed that older users would prefer having navigational elements at the center of web interfaces while younger users would prefer the left side of the screen. Therefore, static web platforms with "one-size-fits-all" designs cannot meet these varying needs. This calls for the development of more dynamic and intelligent web platforms.

Web platform designers and developers need to create more intelligent web platforms that can accommodate these diverse preferences. Hence, to address the dynamism in web-platform usage, adaptive and personalized website design would be beneficial (Desai, 2021). This could be achieved by leveraging artificial intelligence through automated detection systems using machine learning algorithms and models that could detect users' characteristics from eye-tracking data and adapt the user interfaces accordingly. For instance, Shojaeizadeh et al. (2019) showed the potential of detecting cognitive demand automatically via eye tracking and the opportunity it provides for designing advanced decision support systems that can provide personalized responses to users. Berkovsky et al. (2019) also revealed how the range of personality traits can be detected using eye tracking data through the potential of machine learning algorithms. Similarly, with classical machine learning algorithms such as random forest and linear regression, Mohammad (2021) showed that users' demographics can be predicted from eye-tracking data. The study concluded that there is a correlation between age and number of fixations. The adaptation of the user interface could also be done by having users define their demographics as a first step before using web platforms. For web platforms that require users to have personal profiles, the adaptation could be done based on users' profile information. These strategies could culminate in offering personalized experiences to different users. Coupled with the outcome of prior studies (Machado et al., 2018; Sili et al., 2016) and leveraging the findings in this study, web developers and designers can develop dynamic web platforms that suit the varying preferences of users using these strategies. For example, Machado et al. (2018) introduced a conceptual framework for developing real-time personalized user interfaces and Sili et al. (2016) introduced adaptation based on user profiles which understanding of demographic variations could help facilitate. To achieve this, in addition to the findings in this study, adequate representation of personnel with diverse demographics that correspond to the various demographics of end-users is recommended in the design team of web platforms. Also, it is recommended that participants of diverse demographic variables which are representative of end-users' demographics should be involved in the user evaluation of web platforms to ensure that various perspectives and perceptions are captured. This underscores the need for iteration in the design of web platforms to ensure that the results of user evaluation are incorporated in new updates of web platforms (Gould & Lewis, 1985). Also, due to the different purposes, functionalities, and visual stimuli of web platforms, an assessment of demographic variations in different contexts is required.

6. Conclusions

This study investigates instructors' demographic variations in user evaluation of a web platform designed to connect with practitioners for student development. The study shows that female instructors had higher fixation counts and statistically longer fixation duration than their male colleagues. Male instructors paid more attention to the name of the practitioner, size, and ethnic diversity of the practitioner's organization than female instructors. Hence, male instructors considered these factors more important while collaborating with practitioners. Although female instructors took longer to complete assigned tasks and reported higher cognitive load, the participants gave higher ratings regarding trust and perceived usability of the web platform compared to male instructors. Compared to Generation Y, Generation X instructors had higher fixation count and longer fixation duration. Generation Y instructors fixated more on the name and position of the practitioner, name, website address, and location of the practitioner's organization than Generation X instructors. Hence, they highly regard these parameters while collaborating with practitioners. Generation X instructors had higher self-reported cognitive load, statistically higher task completion time, and lower ratings for perceived usability and trust compared to Generation Y. The findings of this study regarding age-related differences largely agree with prior studies. However, the findings regarding gender-related differences were both in consonance and at variance with prior studies. This could be attributed to differences in the contexts of inquiry as well as participants' characteristics.

The understanding of demographic variations in web platform perception revealed by this study would be beneficial to stakeholders in the design of new web platforms and the iterative design of existing ones to ensure that the needs of varying categories of users are met. The findings are crucial for designers of web platform designers in developing inclusive systems that meet the various needs of diverse users and offer personalized experiences rather than just the conventional one-sizes-fits-all. The findings could be leveraged in the design of adaptive user interfaces either through real-time personalization or adaptation to user profiles. This could also help enhance web platform usability and facilitate users' acceptance and continual usage.

The study has some limitations which can be addressed in future studies. The study had a relatively small and homogeneous sample (i.e., 20 instructors in similar academic domains from a single university). This may limit the generalizability of the findings to broader populations. In addition, this study only examined demographic differences for age and gender. Therefore, the peculiarities of the study should be considered in the application of the findings. To address the limitations of this study, future studies could explore larger sample sizes comprising very diverse participants with a focus on other demographic differences such as ethnicity, cultural background, and digital literacy. In addition, subjective measures were adopted to assess trust and cognitive load, and objective measures such as pupillometry, dual task, and electroencephalography can be used to investigate demographic differences. Also, future research is proposed to examine age-related differences among participants of the same gender and gender-related differences among participants of the same age group.

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Data availability statement

The data for this study are available from the corresponding author upon reasonable request.

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