Technology Mastery Scale: Validation Across Age and Gender

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Abstract

This study assesses the Technology Mastery (TM) scale, which is designed to subjectively measure technology proficiency and aims to closely align with objective skills. Microsoft Excel was chosen as the first test case because it is commonly used but difficult to master, making it ideal for evaluating the scale's effectiveness. Despite the scales high internal reliability and construct validity, the findings indicate a weak correlation between the scale's scores and actual Excel proficiency, further highlighting the difficulty of creating subjective assessments capable of accurately reflecting true technological mastery. Further analysis revealed that participants often underestimated their Excel skills, with this trend more pronounced among women, yet there was a shared understanding of what average Excel users can and cannot do. The primary limitation of the study was the lack of participation from advanced and expert Excel users, which might have influenced the results. This study's initial test of the TM scale highlights the complexities in measuring technology mastery and points to the need for further validation across various technologies and user skill levels. In order to improve predictive accuracy and relevance, future revisions of the TM scale should heavily incorporate perspectives from verified technology experts.

Introduction

Historically, technological advancements from the 20th to the 21st century have been marked by innovations that have reshaped society, with the internet providing universal access to information and AI pushing the boundaries of human-machine interactions (Martín-Gutiérrez et al., 2017). Disparities in technology integration and mastery are evident across various demographic groups (Kim & Padilla, 2020; Mossberger et al., 2008; Vekiri & Chronaki, 2008).

Technology is essential in every facet of our professional and personal lives, demanding mastery across all domains (Cooke et al., 2019; Instefjord, 2014; Saffari et al., 2014). Challenges arise due to age and gender biases in technology design and societal norms, leading to disparities in technology adoption and proficiency (Morris et al., 2005; Perry & Greber, 1990; Vekiri & Chronaki, 2008). While younger individuals often integrate new technologies into their lives with ease, older adults might face significant barriers, creating a pronounced gap in technological proficiency (Czaja et al., 1995, 1998; Mead et al., 2000; van Dijk, 2006). Furthermore, when gender disparities intersect with these challenges, the result is an amplification of existing inequalities in our progressively digital society (Goswami & Dutta, 2016).

In an era where technology is embedded into every aspect of daily life, being able to measure one's technological proficiency has become paramount. Dahlman and Westphal (1981) highlight that technology mastery, being multifaceted and relative, is challenging to quantify. This is because technology mastery is about more than *using* technology to complete tasks; it also requires the ability to *adapt* technologies to various needs and circumstances. While scales for technology adoption (Davis, 1989; Venkatesh et al., 2003) and computer self-efficacy (Compeau & Higgins, 1995) have been developed, a comprehensive measure for technology mastery has remained elusive until recently. Gleaton et al. (2023) have developed a scale that aims to accurately measure technology mastery. Our work emphasizes that true mastery goes beyond individual perceptions, requiring thorough understanding and efficient use of a technology's features in daily life. The ongoing challenge is ensuring our scale is a valid measure of technology mastery, regardless of cognitive biases and individual factors, such as age, gender, and the tendency to provide inaccurate self-assessments. The overall goal is to make the concept of technology mastery more accessible and foster deeper, more meaningful engagement with technology.

Defining Technology Mastery

Technology Mastery is not just about how well someone uses technology but extends to how seamlessly an individual integrates technology into their daily life. Dahlman & Westphal (1981) were among the pioneers in this field, defining technology mastery as "the ability to make effective use of technological knowledge... [the] information about physical processes which underlies and is given operational expression in technology" (p. 13). They emphasized the importance of applying this knowledge in diverse contexts, suggesting that mastery is achieved when knowledge is actively tested and applied in problem-solving scenarios involving technology. They also raised concerns about the challenges of quantifying such a multifaceted concept. A well-crafted scale for technology mastery should measure not just how efficiently someone uses technology, but also how well they understand it, adapt it, and apply it in various situations.

Building on this foundation, Aldridge (1983) introduced the concept of "mastery learning." While Dahlman and Westphal (1981) focused on the application of knowledge, Aldridge highlighted three main factors: the time spent learning, the learner's motivation, and what the learner already knows. This idea suggests that measuring tech skills should involve considering the user's background, level of motivation to master the technology, and duration of time spent engaging with it. Therefore, true technology mastery considers not just skill but also the learner's background and experiences.

Venkatesh et al. (2003) expanded on these insights through the development of a scale that aimed to consolidate various models that explored why people choose to adopt or reject technology. The result, the Unified Theory of Acceptance and Use of Technology (UTAUT), identifies four primary determinants influencing an individual's decision to use technology: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. Each of these determinants not only speaks to the initial adoption of technology but also to the journey towards mastery. For instance, as individuals become more comfortable (Effort Expectancy) and see tangible benefits (Performance Expectancy) from a technology, they move closer to mastering it. Additionally, the influence of peers (Social Influence) and the presence of supportive conditions can accelerate this process. Venkatesh et al. (2003) offers a comprehensive perspective of technology use that bridges the gap between technology adoption and mastery.

The UTAUT model emphasizes the role of facilitating conditions, which are defined as aspects of the technological environment that support the use of the system (Venkatesh et al., 2003). This implies that the technology’s system and support as well as organizational support are crucial in aiding users to not only adopt but to also continue using and eventually mastering technology. Social influence, which refers to how peers’ opinions are valued, is particularly significant in the early stages of technology use, where individuals might lack comprehensive knowledge about the technology and therefore, rely on peer advice and experiences. The UTAUT model, while focusing on initial adoption, also provides a pathway for exploring the progression towards mastery by considering how these determinants influence sustained and advanced use of technology. The model suggests that the proposed determinants of usage can explain up to 70% of the variance in behavioral intention to use a system and about 50% of the variance in actual use, indicating a substantial influence on technology use behaviors (Venkatesh et al., 2003). This suggests that the determinants identified by UTAUT not only facilitate initial adoption but also pave the way towards continued and advanced use.

While models like UTAUT lay the groundwork for understanding technology adoption and its progression towards mastery, the expansive and varied uses of technology today necessitate a broader range of perspectives to truly comprehend mastery. Satterfield et al. (2021) took a unique approach to defining mastery of assistive technology by consulting experts in the field. Their research led to the coining of the term "power user," which goes beyond the traditional understanding of someone proficient with technology. Instead, a "power user" is someone for whom technology becomes second nature, almost an extension of themselves. This profound connection with technology signifies a level of comfort and subconscious use, highlighting the depth of their mastery. Satterfield et al. (2021) provided a structured roadmap to achieving this level of mastery. They identified distinct stages where an individual traverses on their journey to becoming a technological master. These stages, ranging from 'emergent' to 'independent', offer a clear progression of skill acquisition and application. Their research also pinpointed key predictors of technology mastery, such as the opportunity to use tech, knowledge of tech options, problem-solving abilities, and motivation. These predictors not only align with insights from previous studies but also add depth to our understanding of the factors that influence an individual's journey toward technology mastery.

Ultimately, technology mastery is a multifaceted concept. Beyond mere proficiency, technology mastery encompasses a deep understanding and application of technology, integrating it seamlessly into daily life. It is impacted by many factors including an individual’s motivation, time spent learning, social influences, perceived benefits and ease of technology use.

Determinants of Technology Mastery

Technological Determinants

Several key studies shed light on the intricate factors that influence an individual's path to mastering technology. First, Davis (1989) discusses the importance of perceived usefulness and perceived ease of use as pivotal factors in technology acceptance. His work suggests that for technology to be fully integrated into one's daily life, it must be perceived as both useful and user-friendly (Davis, 1989). This foundational idea resonates with the broader goal of technology stakeholders: to have users not only adopt but master their products. Mastery, in this context, goes beyond mere acceptance; it is the culmination of extensive use and integration of technology into one's life. Davis's emphasis on the correlation between perceived usefulness and frequency of technology use provides a compelling argument for its inclusion as a determinant of technology mastery.

Compeau & Higgins (1995) introduce another layer to this discourse with their exploration of computer self-efficacy. Their study highlights the impact of an individual's belief in their ability to use technology effectively. This self-efficacy, encompassing dimensions like magnitude, strength, and generalizability, plays a pivotal role in determining one's engagement with technology (Compeau & Higgins, 1995). The significant relationship they identified between positive emotions towards computers and actual computer usage further cements the idea that personal beliefs and attitudes are integral to technology mastery.

Group Determinants

Mastering technology, a valuable skill in our digital age, is influenced by a variety of group determinants, including age, gender, race, and socio-economic background. This study will spotlight age and gender due to constrained variation among the study population in other demographic factors. However, it is pivotal that future studies explore and validate the technology mastery scale across a wider demographic spectrum to ensure comprehensive insights.

Age has often been identified as a barrier to technology mastery. However, research suggests a more complex relationship between age and technology mastery. Czaja et al. (1995; 1998) found that while age-related differences in attitudes toward computers are present, when experience with computers was controlled for, age did not significantly influence attitudes. This aligns with the findings of Neves et al. (2018), who argue against the common portrayal of older adults as a homogenous group characterized by technophobia and digital illiteracy, emphasizing the need to consider personal contexts in technology adoption among this demographic. Practical experience with technology becomes a more defining factor than age in shaping one's proficiency, especially when performance is not strictly tied to physical and cognitive challenges. Despite the potential for mastery, older adults continue to utilize available technology significantly less than their younger counterparts (Walker et al., 2019). It is crucial to ensure that research takes into consideration the complex nature of technology adoption and use among older adults. In turn, this research can inform future interventions and policies that can aid in efforts to facilitate technology mastery across all age groups.

Gender disparities in technology attitudes, adoption, and usage have also been a focal point of research. Goswami and Dutta (2016) provide a comprehensive exploration of this topic, revealing that while women and men both engage with technology, the nature and depth of their interactions differ considerably. For instance, while men often adopt technology based on personal decisions, women's interactions with technology are more influenced by social factors. This is evident in areas like e-commerce, where women are reportedly more influenced by online consumer reviews, especially negative ones, compared to men who might be more driven by the product's specifications or brand reputation (Goswami & Dutta, 2016). Furthermore, going from childhood to adolescence, there tends to be a noticeable drop in technology interest among girls, whereas boys' technology interest remains relatively steady (Calvert et al., 2005). This divergence in early life can have lasting implications on technology adoption and proficiency in adulthood. Goswami & Dutta (2016) further highlight that women tend to report higher levels of computer anxiety and nervousness and lower affinity towards technology than men.

These findings highlight the importance of developing measures and interventions that take into consideration the influence of gender on technology use. Perry and Gerber (1990) emphasized the need for a feminist perspective in understanding the implications of computer technology, arguing that societal structures, particularly those rooted in patriarchy, influence how technologies are deployed and who benefits from them. A technology mastery measure should not be overly reliant on traits like perceived usefulness, technology confidence, and perception of technological outcomes, which have been shown to be more aligned with and predictive of male behaviors (Goswami & Dutta, 2016). Instead, by acknowledging that social influence and perceived ease of use are paramount, especially for women, we can work towards creating a technology mastery scale that is universally applicable. This approach, rooted in a comprehensive understanding of gender dynamics, can pave the way for a more inclusive technological landscape for all.

Morris et al. (2005) provide further insight into the relationship between age, gender, and technology mastery. Their findings indicate that as workers age, gender differences in technology perceptions become more evident. Specifically, older men tend to prioritize their attitudes, which refer to their positive or negative feelings towards technology use, while older women consider a wider range of factors. Among these factors are the subjective norm, which is the perceived social pressure they feel from their peers and superiors regarding technology use, and perceived behavioral control, which encompasses their assessment of the ease or difficulty of using technology and the resources available to them. Interestingly, younger workers display a unisex pattern, where gender differences in technology perceptions are not as pronounced, suggesting a shift towards more similarity in technology adoption and use between younger men and women. This research emphasizes the importance of age and gender as crucial determinants in shaping technology mastery, each with its unique influence.

While this study places a focus on age and gender, it is also important to acknowledge the significant roles of other individual differences. For instance, race and geographical location also play a significant role in technology access and proficiency. Mossenberger et al. (2006) highlighted a paradox wherein African Americans and Latinos, despite having positive attitudes towards technology, encounter challenges in obtaining equal access and skill. This discrepancy goes beyond just socio-economic factors, pointing towards deeper societal and environmental causes, such as racial segregation and concentrated poverty. Additionally, socio-economic status, often intertwined with race and gender, emerges as a significant determinant. Kim & Padilla (2020) emphasized the gap between available technology in classrooms and its utilization, highlighting the need for comprehensive teacher education programs. Sax et al. (2001) further illuminated the disparities arising from race, class, and gender, revealing that students from low-income backgrounds often lack exposure to essential technological tools.

Importance of Technology Mastery

The rapid evolution of the technological landscape necessitates the development and validation of a context-independent technology mastery scale. As new technologies, platforms, and tools emerge, a standardized measure of mastery across these innovations becomes imperative. Such a scale would not only gauge proficiency but also ensure that the transformative potential of these technologies is harnessed to its fullest, fostering inclusive, dynamic, and future-ready technological landscapes (Martín-Gutiérrez et al., 2017). The rise of virtual and augmented reality technologies, as noted by Martin-Gutierrez and colleagues (2017), showcases the growing importance of these tools in the educational sector. Investments in virtual content creation hit an impressive $1.2 billion in 2016 and were projected to grow to $120 billion by 2020 (Martín-Gutiérrez et al., 2017). Moreover, the surge in AI-related activities and investments has been notably significant, with a substantial increase in AI-related startups, patent counts, and robotics shipments (Furman & Seamans, 2019). The advancements in AI have not only enhanced technical capabilities, such as reducing error rates for image recognition from 29% to less than 3%, but have also manifested in various applications including chatbots and virtual assistants (Furman & Seamans, 2019). As more revolutionary technologies become integral to every facet of education, the need for a technology mastery scale becomes evident. This need is not just limited to knowing how to use them; it is about grasping their educational values, understanding potential challenges, and considering ethical aspects.

Exploring the realm of education technology directly showcases the vital role of technology mastery in enhancing performance. The mastery of educational technology is identified as a crucial yet often overlooked competency for faculty members (Saffari et al., 2014). Advancements in educational technology and e-learning have created an environment that makes educational objectives, such as self-directing learning and immediate feedback, more attainable. Moreover, with students often being familiar with and expectant of these technologies, faculty members must bridge the gap between their technological proficiency and students' expectations by mastering not only the technology but integrating it meaningfully into their teaching methodologies (Saffari et al., 2014; Instejford, 2014). This is a crucial idea to take into consideration when developing a valid self-measurement scale for technology mastery, emphasizing the importance of both technical proficiency and the integration of technology into applicable practices.

Developing a Nuanced Technology Mastery Measure

Navigating Scale Development

Developing a scale, especially one that reliably measures the intended construct, involves a careful, three-phase process: item generation, scale development, and scale evaluation (Boateng et al., 2018). The evaluation phase is crucial, ensuring the scale accurately measures the intended construct through tests of its dimensionality, reliability, and validity (Boateng et al., 2018). However, scale development isn't without challenges. Morgado et al. (2017) highlighted ten primary limitations in scale development practices, such as sample characteristic limitations, methodological constraints, and psychometric issues. They also emphasized the importance of recognizing and addressing these limitations. For instance, ensuring a diverse sample, defining the scale's scope, and employing both qualitative and quantitative methods can mitigate some of these challenges (Morgado et al., 2017). Neutral question framing can reduce social desirability bias, and items should be updated regularly to remain relevant in rapidly evolving fields like technology (Morgado et al., 2017). A balance between scale brevity and comprehensiveness is essential, and uncontrollable variables should be acknowledged (Morgado et al., 2017). Lastly, providing a detailed manual is crucial for guiding users in scale application and interpretation

(Morgado et al., 2017). While scale development is a rigorous process, recognizing and addressing potential limitations ensures the creation of reliable and valid measures.

The Development of the Technology Mastery Scale

In our pursuit to understand technology mastery, Gleaton et al. (2023) conducted a study where undergraduate participants and the research team's family members were interviewed about their perceptions and experiences with technology mastery. A recurring theme from the participants was the association of technology mastery with knowledge, particularly the knowledge of troubleshooting techniques and awareness of device features (Gleaton et al., 2023). Interestingly, when participants discussed technologies they felt they had mastered they frequently mentioned tools they used daily, such as specific apps, programs, phones, and computers. This observation aligns with existing literature that posits consistent and frequent use of technology enhances comfort and performance with it. Motivations for mastering technology were predominantly driven by its utility as a tool to augment life, work, and overall productivity, with consistent use and comfort with the technology being key indicators of mastery. Conversely, technologies perceived as complex or having a steep learning curve often faced abandonment before mastery was attained.

In the next study, we began the scale development process. Drawing from the definitions and themes identified in the first study, a comprehensive item generation phase was initiated, resulting in a survey with over 500 items (Madera et al., 2023). Participants were prompted to reflect on a technology they had either mastered or not, contingent on the context of the item. A principal component analysis (PCA) followed by a confirmatory factor analysis (CFA) was conducted, reducing the items down to 36 with an eigenvalue of 0.7 or higher. To finalize the list, subject matter experts (SMEs) in Engineering Psychology, adept in the assessment of technological performance from both subjective and objective perspectives, were consulted. Drawing from their expertise, coupled with insights from previous research and our experiences, the items were further refined to a final list of 18 items. This technology mastery scale, rooted in rigorous research and expert insights, aims to provide a comprehensive understanding of technology mastery, capturing both the motivations and barriers associated with it (Appendix A).

Validating the Technology Mastery Scale

Validation is crucial in developing a trustworthy measurement tool, especially in fields like Human-Computer Interaction (HCI) and psychology, where we often turn subjective experiences into quantifiable data. The Dunning-Kruger effect, which describes the tendency of individuals to overestimate their capabilities when their actual knowledge is limited, highlights the possible inaccuracies in self-assessments and how in the absence of a thorough validation process, a scale might seem accurate when it is not (Dunning, 2011; Boateng et al., 2018). Therefore, a mindful validation process, which is cognizant of the Dunning-Kruger effect and other cognitive biases, is imperative to ensure that our technology mastery scale accurately reflects true mastery without being skewed by overconfidence or misrepresentation.

Minimizing the Effect of Cognitive Biases

Cognitive biases, like the Dunning-Kruger Effect, create significant challenges in accurate self-assessment and, by extension, in validating a technology mastery scale. This effect, where individuals with limited knowledge in a domain overestimate their abilities and experts tend to underestimate their capabilities, has been well documented (Dunning, 2011; Moore, 2011; Coutinho et al., 2020). The technology mastery scale must be validated with an awareness of these cognitive biases, ensuring it serves as a reliable metric that reflects genuine mastery rather than perceived competence, across diverse domains and demographic groups.

Karnick et al. (2021) highlighted cognitive bias in technical skill self-assessment among first-year surgical residents, revealing that higher performers, in particular, tended to underestimate their performance. This insight is crucial for technology mastery scale validation, emphasizing the need to ensure that the scale accurately reflects actual skills and technology integration into daily life, rather than merely technological self-efficacy and general under or overestimation, which can be influenced by cognitive biases.

Incorporating insights from Wammes et al. (2021), it is crucial to weave in practical tasks that reveal real technical skills when validating a technology mastery scale, ensuring a bridge between what people think they can do versus what they actually do. For instance, instead of merely asking individuals to rate their estimated proficiency in a software, the scale validation process should involve having them complete specific tasks within a software to objectively measure their skill level. Wammes et al. (2021) highlighted the difficulty educators face in accurately assessing students' technological skills, especially considering that many technical skills are often not observable in educational contexts. Therefore, ensuring our technology mastery scale is grounded in actual performance metrics can protect the scale from various cognitive biases and ensure its usefulness and reliability in various technology use contexts.

While actual performance metrics are essential, it is equally crucial to consider the influences of gender perceptions on self-assessment. Bench et al. (2015) explored positivity bias and found that men tend to overestimate their past performances in mathematics more than women, which could contribute to the gender gap in STEM fields. This overestimation by men accounted for their greater intent to pursue math fields compared to women. The findings suggest that gender gaps in STEM fields might not necessarily be due to women underestimating their abilities, but rather might be due to men overestimating theirs. Similarly, Venkatesh et al. (2005) highlighted that such gender-driven overestimations also play a role in technology adoption decisions in the workplace, suggesting a broader pattern where gender perception influence both STEM pursuits and general technology use. The impact of gender perceptions on STEM and technology adoption highlights the need for research methodologies that integrate women from the beginning, both in their role as participants and through the consideration of gender as a covariate in data analysis, to ensure the development of the technology mastery scale is unbiased and valid.

In the context of technology mastery, Burson et al. (2006) posited that the Dunning-Kruger effect might not be universally applicable. If a task is perceived as moderately difficult, both low and high performers' self-ratings tend to be accurate. This suggests that the Dunning-Kruger effect might not be as pronounced in areas like technology mastery, which is often perceived as challenging. The authors also introduced the noise-plus-bias model of judgment to explain the Dunning-Kruger effect, emphasizing the importance of comparing oneself to their perception of the "average" rather than evaluating personal confidence against performance (Burson et al., 2006).

As technology becomes increasingly personalized, what constitutes "average" use becomes ambiguous. While professionals in fields like aerospace engineering or marketing might use technology in different ways, each can demonstrate mastery in their respective domains, even though they can utilize different applications and functionalities of the same technology. The technology mastery scale must be firmly rooted in actual performance results and remain impartial to cognitive biases that individuals might be predisposed to due to their knowledge level, background, or gender. The undeniable presence of these biases highlights the inherent challenges involved in developing a technology mastery scale that is accurate across various technologies and contexts. Ensuring that the technology mastery scale results are not influenced by cognitive bias is paramount for accurate and trustworthy evaluations.

Study Objectives

RQ1. How is actual technology performance related to scores on the technology mastery scale?

RQ2. What is the relationship between individuals' self-estimated technological proficiency and their actual performance results?

RQ3. How accurately do individuals perceive the technological skill level of the 'average' user, and how do they assess their own performance in relation to this perceived average?

Through these questions, our aim was to rigorously validate the technology mastery scale, ensuring it could be as a reliable tool for educators, employers, and individuals alike. In doing so, we hoped to provide a quick and reliable tool that aids individuals in not only gauging their proficiency with technology, but also enhancing their mastery of the many technological tools they engage with daily.

Methods

Participants

This study recruited participants on the online study platforms: Prolific and SONA. To be eligible for participation, participants were required to be living in the U.S. or Canada, be at least 18 years of age, and have access to Microsoft Excel. Participants from the two platforms were combined to form a sample of 245 participants of which 48% were female and 52% were male, ranging in age from 18 to 72 ($\bar{x}$ = 34.19; $S\chi$ = 13.41), and included the following ethnic backgrounds: 19% Asian, 16% Black/African American, 57% Caucasian, 9% Other. The sample included mainly participants with some college (28%), a bachelor's degree (33%), or a graduate degree (15%). Participants reported having used excel for a range of 0 to 35 years ($\bar{x} = 9.42$; $S\chi = 7.91$), with most participants stating they use Microsoft Excel less than once a month (42%) , 1 to 3 times a month (22%), or 1-3 times a week (20%).

Materials

A Qualtrics survey was developed and utilized to collect data. The survey consisted of various sections including demographics (Appendix B), Technology Mastery Scale (Appendix A), and a 30-question Microsoft Excel assessment (Appendix C). The Excel assessment was derived from supplemental materials and practice questions for the Microsoft Office Specialist (MOS) certification for Excel Associate and Excel Expert levels. Additional scales and measures will be included to explore relationships to Problem-Solving (Heppner & Petersen, 1982), General Self-Efficacy (Schwarzer, 1992), Technology Self-Efficacy (McDonald & Siegall, 2001), Technology Acceptance (Venkatesh et al., 2003) and System Usability (Brooke, 1995). The results of our Technology Mastery scale will also be compared to results on the Continuum of Assistive Technology Mastery (Satterfield et al., 2021). To address my hypotheses, participants have been asked the following questions:

1) How many questions do you think you answered correctly on the Excel task? [0-30 slider]
2) How would you rate your mastery of Excel? [Novice; Intermediate; Advanced; Expert]
3) What percentage of other study participants do you believe you outperformed on the Excel task? [0-100 slider]
4) How many questions do you think the average Excel user would answer correctly? [0-30 slider]

5) Please name and briefly describe 3 tasks that you believe the average Excel user would be able to accomplish in Excel. [3 text entry boxes]
6) Please name and briefly describe 3 tasks that you believe the average Excel user would NOT be able to accomplish in Excel. [3 text entry boxes]

Procedure

To initiate the study, the Qualtrics survey was posted on recruitment platforms, SONA and Prolific. Participants needed to provide their informed consent and meet the inclusion criteria to proceed with the survey (Appendix D). The survey prompted participants to provide their demographic information, answer the Tech Mastery scale questions with regards to Excel, and complete a MOS Excel assessment. It was anticipated that there would be a significant strong positive correlation between participants' TM scale scores and MOS Excel test scores for all participants, regardless of age or gender.

H1A. Scores on the Technology Mastery scale will significantly correlate with MOS Excel test performance.

H1B. Scores on the Technology Mastery scale will significantly correlate with MOS Excel test performance for both women and men.

H1C. Scores on the Technology Mastery scale will significantly correlate with MOS Excel test performance regardless of age.

Following the Excel test, participants completed a self-assessment section where they were asked to guess their accuracy out of 30 questions and rate their Excel skills from novice to expert. It was anticipated that participants involved in the study would generally be non-experts and therefore be more likely to overestimate their performance. Participants' degree of overestimation was expected to vary depending on their gender and age.

H2A. Given that most participants are expected to be non-experts with the technology, there will be a tendency for individuals to significantly overestimate their technological abilities in their self-assessments compared to their actual performance.

H2B. Women's self-assessment will significantly align more with their actual performance compared to men who will likely overestimate their technological proficiency.

H2C. Younger and older age groups will demonstrate statistically significant differences in the accuracy in various age groups' self-assessments compared to their actual performance.

The self-assessment section also asked participants to compare their skills to their perception of an average Excel user and then prompted them to describe the Excel tasks the average Excel user can and cannot accomplish. It was predicted that participants will inaccurately estimate their ranking among peers. The accuracy of their estimate of where they place in relation to the average is expected to vary depending on their gender and age.

H3A. There will be a significant difference between participants' estimated percentile scores and their actual percentile scores.

H3B. Women will estimate their percentile scores more accurately than men, demonstrating a significantly smaller difference between their estimated and actual percentile scores.

H3C. There will be significant differences between younger and older age groups' estimated percentile scores and their actual percentile scores.

The survey went on to measure problem-solving, technological self-efficacy, general self-efficacy, technology acceptance, and system usability using responses to validated scales. The average duration of time to complete the survey was 27 minutes, and participants were compensated with either 1.0 SONA credit or at a rate of $12 per hour.

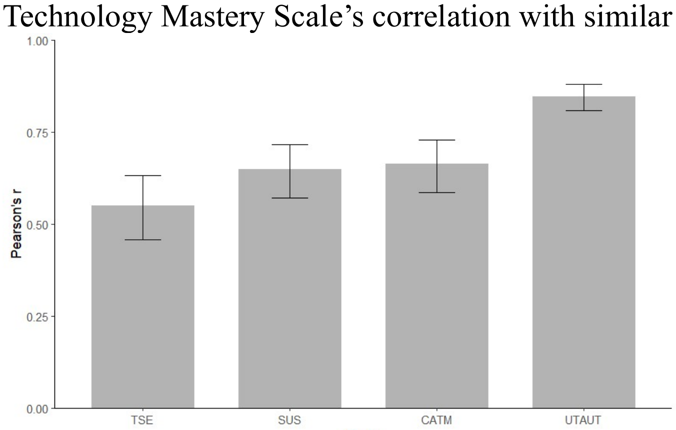
Results

Ensuring data and scale quality

In the initial phase of analysis, we underwent a data cleaning process to ensure we were working with high quality data. We identified and excluded participants from the final dataset if they did not complete the survey, did not pass attention checks, or showed a tendency to provide identical responses to all items. To score the TM scale, the sum of the 18 items was calculated for each participant.

To begin testing the validity of the TM scale, a principal component analysis (PCA) was conducted once again to ensure the reliability of the technology mastery (TM) scale. Each scale item presented an eigenvalue above 0.7, except for item 8: “I wanted to try it out”. The PCA revealed the same three factors with the same items categorized into each factor. The TM scale also demonstrated high internal consistency with a Cronbach’s alpha score of .84. Additionally, the TM scale proved to have significant convergent validity as it was significantly correlated with related measures such as UTAUT (r = .85, p < .001), CATM (r = .66, p < .001), SUS (r = .65, p < .001), and TSE (r = .55, p < .001).

Figure 1.
Technology Mastery Scale’s correlation with similar scales



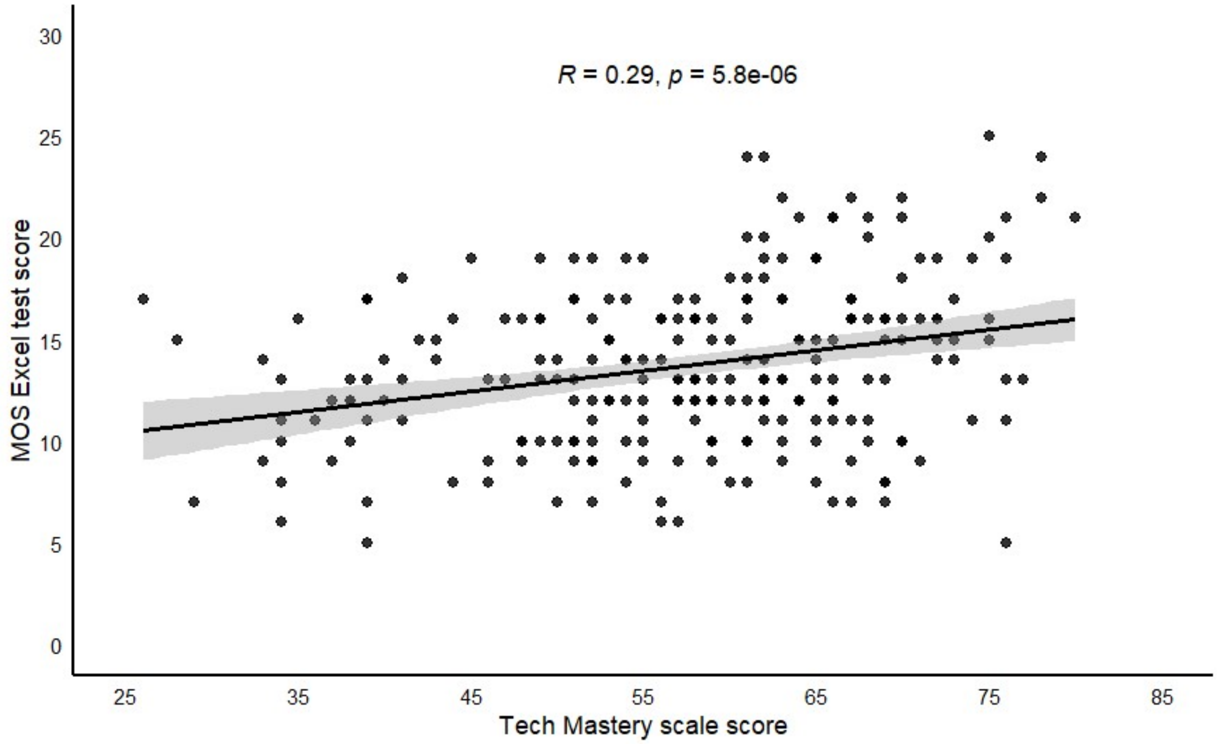
Note. The Technology Mastery scale was shown to have statistically significant strong positive correlations with all four similar scales measured in this study.

Before further analysis could be conducted, the reliability and validity of the MOS Excel test needed to be established. Each of the 30 MOS Excel test questions were scored and coded as either correct (1) or incorrect (0); no partial credit was given. An overall MOS Excel test score was then calculated by summing the value of each question. The MOS Excel test was found to be internally consistent with a Cronbach's alpha value of .66 indicating moderate reliability. An item analysis was performed on the MOS Excel test; a point bi-serial correlation between the item score (1 or 0) and the overall MOS Excel test score provided a discrimination index for each item. With the exception of questions 1.2, 3.5, and 4.8, most items demonstrated correlations above .2, aligning with Evans' (1996) standard for satisfactory item performance (Appendix E). Interestingly, MOS Excel performance did not have a strong positive relationship to frequency of use (r=.25, $p < .001$) and number of years excel was used (r=.30, $p < .001$).

Tech Mastery Scale vs. MOS Excel Results

To address RQ1 and its associated hypotheses (H1A, H1B, H1C), a Pearson correlation analysis was conducted to compare participants' actual performance scores on the Excel task (ranging from 5-25) with their scores on the technology mastery scale (ranging from 26-80). The MOS Excel test scores displayed a weak yet significant correlation with Technology Mastery scale scores ($r = .29$, $p < .001$).

Figure 2.
Comparing Technology Mastery scale scores and MOS Excel scores



Note. This figure demonstrates the relationship between TM scores and Excel scores. As is evident, there is not a strong, positive correlation between the two values as expected. Self-reports detailing perceived mastery do not have the capability to reliably predict actual performance.

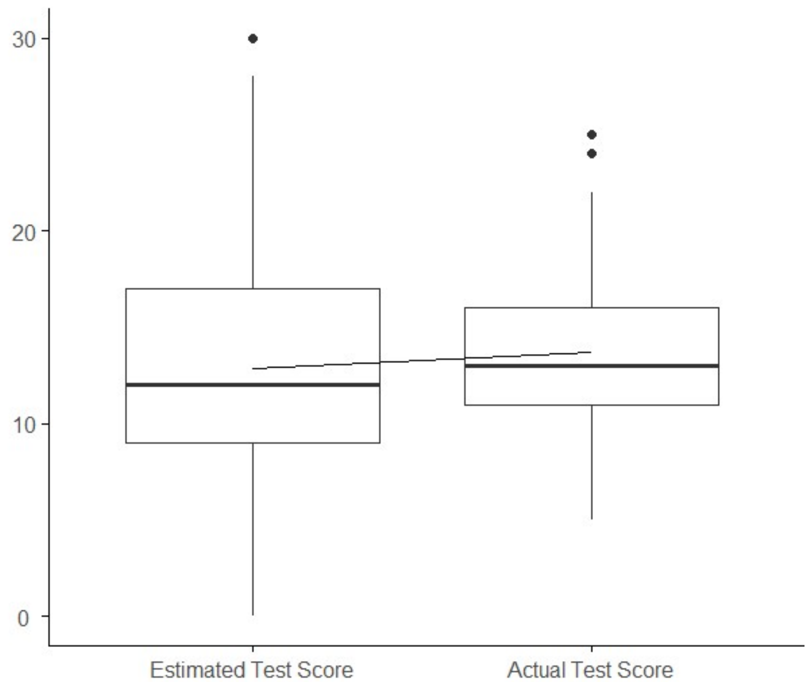
To assess whether gender moderates the association between performance on the Excel test and Technology Mastery (TM) scores, separate Pearson correlations were conducted for men ($r = .22$, $p = .012$) and women ($r = .37$, $p = < .001$), which revealed that both genders exhibited a significant weak positive relationship between Excel performance and TM scores. When examining age as a predictor variable in the linear regression model with TM as the dependent variable, the unstandardized regression coefficient for age was not statistically significant (β =0.003, $p = .95$). This indicates that age did not appear to have a statistically significant impact on the relationship between TM and MOS Excel scores. To further investigate the impact of age, correlations between TM scale scores and actual performance for each age group were calculated. Significant yet weak positive correlations were found for the three age groups analyzed, which include young adults under 30 ($r = .22$, $p = .02$), middle adults between 30 and 49 ($r = .33$, $p = .001$), and older adults aged 50 and over ($r = .32$, $p = .04$). These findings suggest that scores on the Tech Mastery scale are not valid predictors of actual technological proficiency with specific regards to Microsoft Excel. This result is not moderated by gender or age.

Self-estimated vs. Actual Performance

To address RQ2 and its associated hypotheses (H2A, H2B, H2C), a paired sample t-test was conducted to compare participants' self-estimated performance on the Excel test with their actual scores. The results revealed a statistically significant difference ($t(244) = -2.39$, $p = .018$, $d = -.153$), indicating a tendency for participants to inaccurately estimate their performance. Descriptive statistics further illustrate this pattern, with participants generally estimating their performance to be lower ($\bar{x} = 12.83$, $S\chi = 6.50$) than their actual performance scores ($\bar{x} = 13.72$, $S\chi = 4.00$), suggesting a trend towards underestimation of their abilities (Figure 3). Furthermore, participants' self-assessed competency in Excel, ranging from Novice to Expert, was correlated with their scores on the MOS Excel test, revealing a significant moderately positive relationship ($r = .44$, $p < .001$).

Figure 3.

Comparing MOS Excel Test Post-test Estimations and Actual Performance

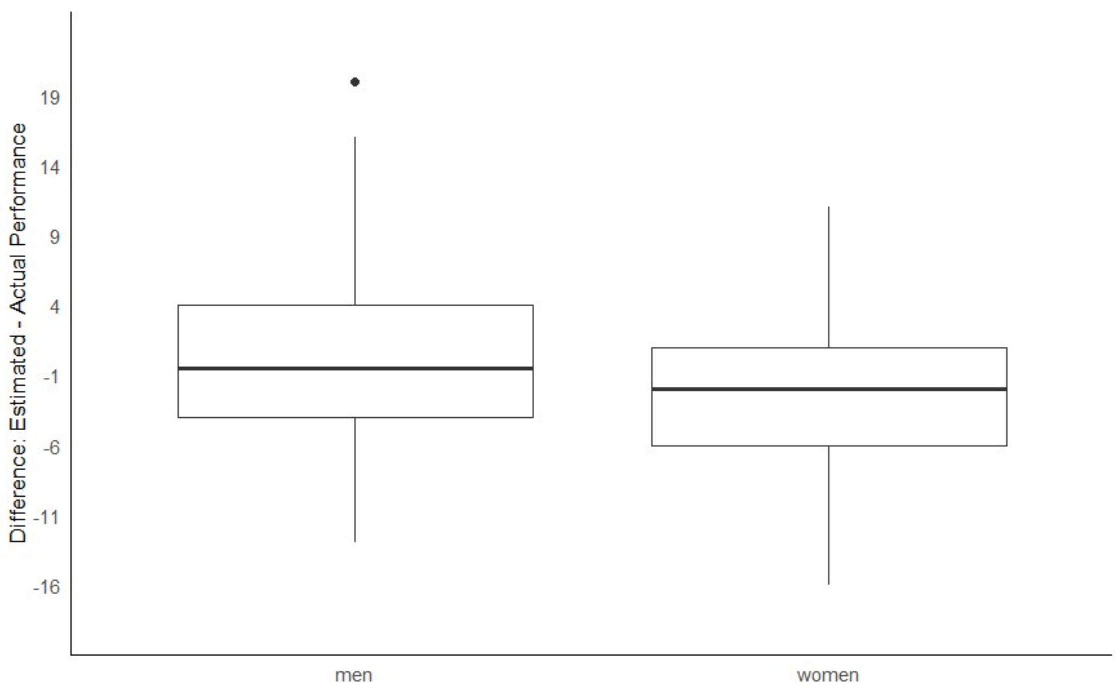


Note. Participants' post-test estimations were slightly but significantly less than their actual MOS Excel scores.

The analysis concerning gender revealed that men (coded as 1) and women (coded as 2) differ significantly in the accuracy of their self-assessment relative to their actual performance. An ANOVA revealed that gender significantly influences the difference between estimated and actual performance ($F(1, 243) = 17.97$, $p < .001$). Descriptive statistics for the difference in estimated from actual performance indicated that men had a mean difference close to zero ($\bar{x}$ = 0.57, $S\chi$ = 6.17), implying a relatively accurate self-assessment on average, whereas women demonstrated a negative mean difference ($\bar{x}$ = -2.49, $S\chi$ = 5.00), reflecting a tendency to underestimate their performance. These differences were found despite no statistically significant difference among actual performance ($F(1, 243) = .051$, $p = .82$) between men ($\bar{x}$ = 13.77, $S\chi$ =

4.12) and women ($\bar{x}$ = 13.66, Sχ = 3.79). This gender disparity highlights a subtle but significant difference in self-evaluation accuracy, where, more so than men, women tended to believe they performed worse than they actually performed (Figure 4). In contrast, age, when treated as a covariate in linear regression, did not significantly predict the accuracy of self-assessment compared to actual performance ($\beta = 0.033$, $p = .24$), indicating that across the age spectrum, the precision of self-assessment remained statistically unvaried. To further support this finding, a 2 (estimated vs actual performance) x 3 (age group) ANOVA revealed nonsignificant differences between estimated and actual performance and each age group ($F(2, 242) = 1.49$, $p = .23$). Each age group young adults ($\bar{x}$ = -1.13, Sχ = 5.75), middle adults ($\bar{x}$ = -1.00, Sχ = 6.35), and older adults ($\bar{x}$ = .02, Sχ = 4.78) overall presented accurate estimations of their performance.

Figure 4.
Comparing Difference in Estimated and Actual Performance by Gender



Note. Box plots for men and women’s difference in post-test estimations vs. actual scores on the MOS Excel Test

Comparisons to the Average Excel User

The analysis of participants' perceptions of the average Excel user's performance revealed a significant overestimation. After taking the test, participants estimated that the average user would correctly answer approximately 16 questions out of 30, which was significantly higher than the actual average performance ($\bar{x} = 13.72$, $S\chi = 4.00$), $t(244) = 7.35$, $p < .001$, $d = .47$. This result indicates a general tendency among the participants to overestimate the average Excel user's abilities compared to the actual average.

When examining the effects of gender and age on these estimations, the results indicated uniform perceptions across genders, as the ANOVA for gender yielded no significant effect ($F(1, 243) = 0.09$, $p = .77$). Similarly, age did not significantly predict the difference in estimated versus actual *average* performance, as indicated by the results of a linear regression analysis ($\beta = 0.075$, $t(243) = 3.01$, $p = .003$). An ANOVA also found no significant difference between young, middle, and older adults ($F(2, 242) = 3.34$, $p = .037$). These findings suggest that both men and women, regardless of age, are equally likely to overestimate the average Excel user's abilities, which might reflect common societal assumptions about Microsoft Excel proficiency.

When comparing participants' self-assessed percentile ranks with their actual percentile ranks based on performance, a paired sample t-test showed a significant underestimation ($\bar{x} = -9.07$, $S\chi = 38.33$), $t(244) = -3.70$, $p < .001$, $d = -.24$. Further analysis revealed that on average participants ranked themselves in the 41st percentile, meaning they believed they outperformed approximately 41% of their peers in the study, but this does not depict the wide range of estimated percentiles and difference in estimated and actual percentile rankings. The range of estimated percentiles goes from one participant believing they outranked 0% of their peers to one believing they outranked 98% of their peers. The difference in estimated percentile rank vs. actual percentile rank revealed an even wider discrepancy with one participant showing a difference of -95.00 and on the opposite end of the spectrum, another participant showed a difference of 93.90. This discrepancy suggests that participants typically underrate and at times extremely overrate their performance relative to others, highlighting possible misaligned confidence or misjudgment of their own Excel abilities when considering their rank among peers.

The influence of gender on the difference between perceived and actual percentile ranks was not statistically significant ($F(1, 243) = 1.516$, $p = .219$), despite men ($\bar{x} = -6.19$, $S\chi = 39.80$) tending to underestimate their rank less than women ($\bar{x} = -12.22$, $S\chi = 36.57$). Age also did not significantly correlate with the difference in estimated versus actual percentile rank ($\beta = -0.095$, $p = .591$). These results imply that while both genders underestimate their performance, this tendency does not vary significantly with age.

Table 3.
Summary of Findings

Hypothesis	Construct 1	Construct 2	Correlation vs Mean Difference	Moderator	Result
H1A	Tech Mastery scale	MOS Excel - performance	Correlation		Not supported but significant results
H1B	Tech Mastery scale	MOS Excel - performance	Correlation	Gender	Not supported but significant results
H1C	Tech Mastery scale	MOS Excel - performance	Correlation	Age	Not supported but significant results
H2A	Excel test performance	Post-test estimated performance	Mean Difference		Not supported but significant results
H2B	Excel test performance	Post-test estimated performance	Mean Difference	Gender	Not Supported but significant results
H2C	Excel test performance	Post-test estimated performance	Mean Difference	Age	Not Supported
H3A	Percentile score	Percentile estimate	Mean Difference		**Supported**
H3B	Percentile score	Percentile estimate	Mean Difference	Gender	Not Supported
H3C	Percentile score	Percentile estimate	Mean Difference	Age	Not Supported

Perceptions of the Average Users Abilities

A Key-Words-In-Context thematic analysis was conducted on participants' responses to the open-ended questions of three things they believe an average excel user can do and three things they believe an average excel user cannot do (Ryan & Bernard, 2000). Twenty-nine themes were identified and defined for what participant's believed an average user can do and forty-two themes were identified for what was believed an average user cannot do (Appendix F). Notable insights were observed about the perceived capabilities and limitations associated with Excel proficiency among the study's 245 participants. For the tasks that participants believe an average Excel user *can* perform, 'simple formulas' such as sum, count, and average were the most frequently mentioned, with 163 mentions. This suggests a consensus that basic arithmetic operations are within the skill set of the typical Excel user. Other frequently mentioned capabilities include 'creating graphs/charts' and 'inputting data', followed by tasks like 'creating tables', 'sorting/filtering', and 'formatting'. These results highlight that users view Excel as a tool primarily for data management and visualization, with a strong emphasis on organizing and presenting data.

Table 1.
Frequency Table of Excel Activities Average Users Can Do

Excel Activity	Count of CAN_DO	Percentage of CAN_DO
simple formulas	163	21.73%
create graphs/charts	133	17.73%
input data	63	8.40%
sort/filter	51	6.80%
create table	51	6.80%
manage spreadsheet/workbook	49	6.53%
formatting	47	6.27%
formulas	39	5.20%
shortcut keys	36	4.80%
organize data	22	2.93%
manipulate cells	16	2.13%
track financial info	15	2.00%
conditional formatting	11	1.47%
N/A	10	1.33%

Note. Top 14 themes identified by 245 participants who each provided responses to the prompt "Please name and briefly describe 3 tasks that you believe the average Excel user would be able to accomplish in Excel."

When considering tasks that participants think an average Excel user *cannot do*, 'pivot tables' and 'advanced formulas' lead the count, indicating these are perceived as more complex and possibly requiring advanced knowledge of Excel. Additionally, 'macros/VBA' and 'data analysis' are also among the top mentions for challenging tasks, suggesting that automation and in-depth analysis are seen as skills beyond the average user's capability. The presence of 'creating graphs/charts' in both the can-do and cannot-do lists indicates a divergence in perception, where some participants consider chart creation as a basic function. In contrast, others view it as a more advanced feature. Top themes for can and cannot do did not differ for men and women or for the different age groups (Appendix G).

Table 2.
Frequency table of Excel Activities Average Users Cannot Do

Excel Activity	Count of CANNOT_DO	Percentage of CANNOT_DO
pivot table	105	14.00%
advanced formulas	74	9.87%
N/A	71	9.47%
macros/VBA	70	9.33%
data analysis	49	6.53%
create graphs/charts	40	5.33%
Formulas	34	4.53%
create complex visuals	30	4.00%
conditional formatting	23	3.07%
Formatting	19	2.53%
manage data	18	2.40%
sort/filter	17	2.27%
Vlookup	17	2.27%
utilize functions/commands	16	2.13%

Note. Top 14 themes identified by 245 participants who each provided responses to the prompt "Please name and briefly describe 3 tasks that you believe the average Excel user would NOT be able to accomplish in Excel."

Discussion

The purpose of this study was to further explore the relationship between perceived technology mastery and actual technological proficiency. The Technology Mastery (TM) scale was developed through a three-phase process which began with interviews that prompted people to identify the different behaviors and schema they associated with technology they have mastered and technology they had not mastered. Themes were identified and items generated from those themes in phase two. In phase three, the items generated were analyzed and reduced through a series of factor analyses and subject matter expert reviews. The scale development considered a wide range of diverse perspectives on technology mastery to produce a subjective scale that could closely correlate with objective performance.

The TM scale demonstrated good reliability, with a Cronbach's alpha score of .80, indicating high item reliability. Additionally, the scale showed good convergent validity, evidenced by its significant correlations with established measures such as UTAUT, CATM, SUS, and TSE. A principal component analysis further corroborated the scale's construct validity, identifying three factors with all items presenting eigenvalues above 0.7, except for one that has an eigenvalue of 0.66. It is likely that this one item, "I wanted to try it out," scored below the threshold because, if not for school or work, some individuals would not have learned Microsoft Excel to the extent that they did. The consistency of PCA results between this study and a previous study strengthens our confidence in the TM scale as a reliable measure.

Our analysis revealed a significant, yet weak positive correlation between TM scores and actual performance on the MOS Excel test. This outcome suggests that while the TM scale effectively measures perhaps one or more aspects of an individual's relationship with technology, it might not accurately predict actual proficiency. This does not mean that the TM scale is not useful; it just means more analysis is required to understand the applicability of the TM scale and its limitations.

Participants' categorizations of themselves as either a novice, intermediate, advanced, or expert Excel user proved to have a statistically significant moderately positive correlation with TM scale ($r = .45$, $p < .001$) and MOS Excel score ($r = .44$, $p < .001$). This implies that while it is true that people's perception of their mastery typically does not strongly align with their actual performance. Moreover, these results indicate that the TM scale is not solely capturing user's perceptions of their skill level. This might be explained by the high positive correlation with the UTAUT. The UTAUT scale captures four factors: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). It was expected that the TM scale would be closely related to acceptance as individuals are more likely to have mastered a technology if they have accepted that it is beneficial, does not require too much effort, and works within their circumstances; the strong, high positive correlation between UTAUT and TM (r = 0.85, $p < .001$) suggests that the perceptions of mastery that the scale was founded on may be more aligned with acceptance than true demonstrated mastery of technology.

Regarding the discrepancy between participants' self-estimated performance and actual performance, overall, participants underestimated their Excel capabilities, with this trend being particularly pronounced among women despite no difference in actual performance between men and women. These observations suggest that self-assessment of technological proficiency might be influenced by factors beyond actual skill, possibly including stereotypes imposed upon gender identities (Goswami & Dutta, 2016).This theory is supported by many studies that have revealed in the face of negative stereotypes and the emphasis of technology as a male-dominated field, women tend to undermine their performance on technology-related tasks despite showing similar competency to their male counterparts (Cai et al., 2017; Sainz & Eccles, 2012; Stoet & Geary, 2018). This difference could also be a result of varying technology self-efficacy levels among men ($\bar{x}$ = 17.07, $S\chi$ = 3.07) and women ($\bar{x}$ = 15.90, $S\chi$ = 3.56), $t(243)$ = 2.77 , p = .006 , d = .35. The lack of a significant age-related pattern in self-estimation accuracy further indicates that these tendencies are more closely tied to social influences rather than age.

When assessing participant's beliefs about the average Excel user's capabilities. The thematic analysis revealed some common patterns that were consistent across age groups and genders. In general, it is believed that an average excel user should be able to utilize simple formulas, create graphs or charts, and input data. What is considered beyond the average excel user's capabilities is utilizing pivot tables or pivot charts, complex formulas, and coding within

Excel using the macro or visual basic application functionalities. There was minimal overlap between tasks identified within an average user's capabilities and tasks outside their capabilities. Moreover, this coincides with the belief that an average user will answer about half of the questions correctly likely contributed to participants estimating that an average Excel user would correctly answer about 16 out of 30 questions correctly on the MOS Excel test.

These results did not vary between men and women or between different age groups. While consensus about the average Excel user seems to be agreed upon regardless of demographics, perceptions about personal performance in comparison to the average is much more varied. In general, participants underestimated their percentile or the percentage of other study participants that they would outperform. While the average percentile estimation was around 41% and the average difference in estimated vs. actual was approximately 14%, participants responses varied greatly. This again calls into question what factors are contributing to the general tendency to not accurately grasp one's level of mastery; this question is even more puzzling when considering technology such as Microsoft Excel where the capabilities of an average vs an advanced user are unilaterally agreed upon. While age and gender have been previously shown to be significant factors for technology perception and use (Morris et al., 2005), there was not a significant difference of the perception of the average Excel user among men and women or among young, middle, and older adults. Future Technology Mastery scales and programs assessing mastery would benefit from learning what individual factors contribute to a misalignment in perceived vs. actual technological proficiency. Current theories about this misalignment suggest that it might be the result of varied domain knowledge, testing ambiguity, desirability of the tested trait and individual differences such as gender, culture, and ability (Ackerman et al., 2002).

Limitations & Future Research

There are several potential confounds and limitations of this study. To begin with this study only looked at one technology, Microsoft Excel, to begin validating a general technology mastery scale. Microsoft Excel is not representative of technology as a whole. In fact, the majority of participants categorized themselves as either a novice (40%) or intermediate (49%) rather than advanced (10%) or expert (1%) which suggests Microsoft Excel is likely regarded as a rather difficult technology to master. It is reasonable to assume that different technologies studied under the same conditions could result in drastically different results. Another limitation is that the sample consisted of an uneven distribution across age groups, potentially skewing the results towards the perceptions and abilities of middle aged individuals. Additionally, the absence of expert users and limited number of advanced users within our participant pool limits the generalizability of our findings to populations with advanced Excel skills. An even distribution between all levels of proficiency could have altered the results of the correlation between self-assessed and actual technological proficiency. A further limitation stems from the study's oversight of cultural and socio-economic factors; previous research has emphasized these variables as significant determinants of technology adoption and mastery, suggesting that our findings might not fully capture the complexities of technological proficiency across diverse populations. Addressing these limitations in future research would not only enhance the robustness and applicability of the TM scale but also contribute to a more nuanced understanding of the factors influencing technological proficiency and self-assessment accuracy.

Revisions to the TM scale could potentially elicit stronger correlations with objective performance. According to Ackerman et al. (2002), the misalignment between actual abilities and self-reported abilities is likely not due to individuals not knowing what they are capable of; the misalignment is likely more dependent on the knowledge the individual has on the domain in question and the ambiguity or breadth of the domain. Asking an individual about their mastery of an unfamiliar technology, for example a factory machine, will result in them relying on external knowledge they have acquired through media and from others to estimate their level of mastery. This will lead to their perception of mastery being dependent on individual differences and several potentially unrelated sources.

In phase one of the TM scale development, we asked everyday tech users what technology they thought they had mastered and relied on the assumptions that 1) they had mastered three different technologies 2) their definition of mastery was strongly correlated to their own performance. A revised TM scale might have a stronger correlation to performance metrics if themes generated from the opinions of verified experts who regularly showcase their technology proficiency serve as the basis of the survey items. Experts might be a more reliable and consistent source because they are less likely to see the concept of technology mastery as ambiguous.

Conclusion

This study confirms the TM scale as a reliable measure of technology mastery, albeit with limitations in predicting actual technological proficiency. The insights into self-estimation accuracy and perceptions of average user abilities enrich our understanding of the challenges in accurately assessing technology skills. Future research should consider expanding the TM scale to include the original 36 items or should work towards generating new items based on interviews with verified technology experts to explore if this enhances its correlation with technological proficiency. Additionally, replicating this study with different technologies and validating the scale across other demographic features would offer a more comprehensive understanding of technology mastery and its measurement. By addressing these gaps, we can develop more accurate tools for assessing technological proficiency, ultimately supporting the development of targeted educational programs and interventions to enhance technology mastery across diverse populations.

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Appendix A

Technology Mastery Scale

Likert Scale: [1] Strongly disagree [2] Agree [3] Neither agree nor disagree [4] Disagree [5] Strongly disagree

Please rate your level of agreement with the following statements

1) I am more efficient when using the technology.
2) It makes my life easier.
3) This technology optimizes my work output
4) I can now accomplish more daily.
5) I love using this technology.
6) I use[d] this technology to be more productive in my daily life.
7) I enjoy the experience.
8) I wanted to try it out.
9) I am personally motivated to use it.
10) It helped me grow my skillset.
11) This technology makes me feel more competent.
12) It was too expensive.
13) It was not within my budget.
14) The training was too expensive
15) The upkeep was too expensive
16) I did not receive any help from professionals.
17) I did not take any introductory courses.
18) I did not see a need to get formal training for this technology.

Appendix B

Demographics

1. How old are you?

2. How do you identify?
    i. Woman
    ii. Non-binary
    iii. Man
    iv. Prefer to self-describe, below

3. Choose one or more races you consider yourself to be
    i. White or Caucasian
    ii. Black or African American
    iii. American Indian/Native American or Alaska Native
    iv. Asian
    v. Native Hawaiian or Other Pacific Islander
    vi. Other
    vii. Prefer not to say

4. Are you of Spanish, Hispanic, or Latino origin?
    i. Yes
    ii. No

5. What is the highest level of education you have completed?
    i. Some high school or less
    ii. High school diploma or GED
    iii. Some college, but no degree
    iv. Associates or technical degree
    v. Bachelor's degree
    vi. Graduate or Professional degree
    vii. Prefer not to say

6. For approximately how many years have you used Microsoft Excel?

7. How frequently do you use Microsoft Excel?
    i. Less than once a month
    ii. 1-3 times a month
    iii. 1-3 times a week
    iv. Once a day
    v. More than once a day

Appendix C

MOS Excel Test

1. Manage Worksheets & Workbooks

1.1 Why might a cell have a green triangle in the corner? Select all that apply.
a. The cell has incorrect formatting applied.
b. The cell contains an error. (correct answer)
c. The column width is not wide enough to display the data.
d. An inconsistency has been detected. (correct answer)

1.2 Which tab in Excel Options allows you to set your error-checking rules? Select the correct option.
a. Data
b. Proofing
c. Formulas (correct answer)
d. Advanced

1.3 If a cell has a ##### error code, what does it indicate? Select the correct option.
a. The function uses an incorrect operator.
b. The cell has the wrong type of formatting applied.
c. The column is not wide enough to display the cell contents. (correct answer)
d. The cell contains a circular reference.

1. 4 Which of the following statements are true when protecting a worksheet? Select all that apply.
a. You can specify the areas of the worksheet that users can access. (correct answer)
b. Once a worksheet is protected, you cannot unprotect it.
c. You can create a password to access the worksheet. (correct answer)
d. You can only protect a worksheet with a password.

1.5 To create a new workbook: Select all that apply.
a. Go to File > New (correct answer)
b. Select Ctrl+N on your keyboard (correct answer)
c. Select Ctrl+O on your keyboard
d. Go to File > Open

2. Manage Data

2.1 Conditional formatting changes the ________________ of designated cells based on criteria. Select the correct option.
a. content
b. appearance (correct answer)
c. formulas
d. relationship

2.2 What formatting styles are available for conditional formatting? Select all that apply.
a. Color Scales (correct answer)
b. Sparklines
c. Icon Sets (correct answer)
d. Data Bars (correct answer)

2.3 What tools allow you to outline your data? Select all that apply.

a. Group (correct answer)
b. Sum
c. Subtotal (correct answer)
d. Aggregate

2.4 Select the requirements for data grouping. Select all that apply.

a. A label in the first row (correct answer)
b. A total in the last row
c. Similar facts in each column (correct answer)
d. No blank rows or columns in the selected range (correct answer)

2.5 To summarize data, which of the following functions can you use with the Consolidate feature? Select all that apply.

a. Sum (correct answer)
b. Average (correct answer)
c. Product (correct answer)
d. Dividend

3. Manage Tables & Table Data

3.1 PivotTables allow you to ________________ large amounts of data so that it's more easily evaluated and understood. Select the correct option.

a. format
b. organize (correct answer)
c. clean
d. correct

3.2 What type of fields can be grouped? Select all that apply.

a. Date (correct answer)
b. Text
c. Numeric (correct answer)
d. Labels

3.3 What are the data sources that you can use for a PivotTable? Select all that apply.

a. Table (correct answer)
b. Range (correct answer)
c. External data source (correct answer)
d. Grid

3.4 Which of the following options are ways you can name a cell range? Select all that apply.

a. Table Name:
b. Create from Selection (correct answer)
c. Name Box (correct answer)
d. Name Manager (correct answer)

3.5 A table can be converted to which of the following? Select the correct option.

a. Chart
b. PivotTable
c. Data range (correct answer)
d. SmartArt

4. Formulas & Functions

4.1 The result of a formula should be 12/31/2020 and it displays as 44196. Which of the following formats will fix it? Select all that apply.

a. Number
b. General
c. Short Date (correct answer)
d. Long Date (correct answer

4.2 If you use the Ctrl+; keyboard shortcut to enter data into a cell, what would Excel actually enter into the cell? Select the correct option.

a. The current date and time
b. The current time
c. The current date (correct answer)
d. The current hour

4.3 In a VLOOKUP or a HLOOKUP function, what should you enter in the fourth segment of the formula to specify that you want an approximate match return? Select all that apply.

a. True (correct answer)
b. Leave it blank (correct answer)
c. False
d. 1 (correct answer)

4.4 If you configure Excel to update formulas manually, which of the following methods can you use to update the formulas in a whole workbook? Select all that apply.

a. Select F9 (correct answer)
b. Select the Formulas tab, and then select Calculate Now (correct answer)
c. Select the Formulas tab, and then select Calculate Sheet
d. Select Shift+F9

4.5 In which group on the ribbon will you find Remove Duplicates? Select the correct option.

a. Data Types
b. Data Tools (correct answer)
c. Text
d. Formula Auditing

4.6 Which of the following options can Data Validation help with? Select all that apply.

a. Restricting entries in a cell. (correct answer)
b. Guiding users as to what they should enter in a cell. (correct answer)
c. Circling errors on a worksheet. (correct answer)
d. Displaying precedents of a cell.

4.7 Which of the following describes what you can do with Goal Seek? Select the correct option.

a. Find the correct input for the value you want. (correct answer)
b. Create different groups of values or scenarios.
c. Display the results of multiple inputs at the same time.
d. Choose from a list of rules to limit the type of data that people can enter.

**4.8 Which group on the ribbon contains Goal Seek and Scenario Manager?
Select the correct option.**

a. Forecast (correct answer)
b. Data Tools
c. Queries & Connections
d. Get & Transform Data

4.9 Where can you find tools for working with macros, such as Record Macro and the Visual Basic command? Select the correct option.

a. The Data tab on the ribbon
b. The Developer tab on the ribbon (correct answer)
c. The context menu in the worksheet
d. Excel Options

4.10 Which of the following options specifies cell B5 as an absolute reference? Select the correct option.

a. B5 (correct answer)
b. #B#5
c. %B%5
d. (B5)

5. Manage Charts

5.1 To create a chart with a dual axis, what type of chart should you use? Select the correct option.

a. Column chart
b. Combo chart (correct answer)
c. Line with markers chart
d. Area chart

5.2 If you want to expand a PivotChart, you require two or more fields in the ____________ field box. Select the correct option.

a. Filter
b. Legend (Series)
c. Axis (Categories) (correct answer)
d. Values

5.3 Which of the following items can you preview or add using the Quick Analysis tool? Select all that apply.

a. Charts (correct answer)
b. Alt text
c. Conditional formatting (correct answer)
d. Sparklines (correct answer)
e. Images

5.4 Which data arrangement is ideal for a pie chart? Select the correct option.

a. Multiple rows and columns of data.
b. A single row or column of data. (correct answer)
c. A single cell of conditionally formatted data.
d. Any number of rows and columns; however, data must be in a table.

5.5 How does Excel determine what data to use when creating a chart? Select the correct option.

a. It uses all data on the current worksheet.
b. It uses all data in the current workbook.
c. It uses the selected cell and all adjacent cells.
d. It uses only the selected cells. (correct answer)

Appendix D

CONSENT DOCUMENT FOR ENROLLING ADULT PARTICIPANTS IN A RESEARCH STUDY

Georgia Institute of Technology

Georgia Institute of Technology
Project Title: Understanding Mastery of Microsoft Excel

Investigators: *Bruce Walker, Richard Catrambone, Emily Gleaton, Marianna Madera, and Emily Parcell.*

You are being asked to be a volunteer in a research study.

Purpose:
This study aims to better understand how adults (ages 18+) conceptualize "mastery" of technology, specifically, Microsoft Excel. We expect to enroll approximately 200 people in this study.

Exclusion/Inclusion Criteria:
Participants in this study must be 18 or older and must not reside in the European Union or China. You must be fluent in English.

Procedures:
You will be asked to complete questions that pertain to your knowledge of Microsoft Excel and questions that pertain to your belief of what "mastery" entails. Following the questionnaire, you will be asked to complete short tasks in Microsoft excel. The expected duration of the study is approximately 20 minutes.

Risks or Discomforts:
The risk or discomfort of participation in this study is minimal. Risk is no greater than completing day-to-day activities such as using the internet or Microsoft Excel.

Benefits:
You are not likely to benefit in any way from joining this study. We hope that what we learn will someday help develop training materials to foster learning and "mastery" of technology.

Compensation to You:

- You will be compensated $12 per hour for your time and effort. Compensation will be through the Prolific survey platform.
- Instead of monetary compensation, Georgia Tech students will receive 1.0 Sona credits for each hour of participation.

U.S. Tax Law requires that a 1099-misc be issued if U.S. tax residents receive $600 or more per calendar year. If non-U.S. tax residents receive more than $75, mandatory 30% withholding is required. Your address and Tax I.D. may be collected for compensation purposes only. This information will be shared only with the Georgia Tech department that issues compensation, if any, for your participation.

Storing and Sharing Your Information:
Your participation in this study is gratefully acknowledged. Your information/data may be enormously valuable for other research purposes. By providing consent, you are allowing for your de-identified information/data to be stored by the researcher and shared with other researchers in future studies. If you agree to allow such future sharing and use, your entity will be completely separated from your information/data. Future researchers will not have a way to identify you. Any future research must be approved by an ethics committee before being undertaken.

Confidentiality:
The following procedures will be followed to keep your personal information confidential in this study: We will comply with any applicable laws and regulations regarding confidentiality. Your records will be kept under a code number rather than by name to protect your privacy. Your records will be kept in Georgia Tech-approved, password-protected locations. Only study staff will be allowed to look at them. Your name will not be collected, and any other fact that might point to you will not appear when the results of this study are presented or published. The Georgia Institute of Technology IRB and the Office of Human Research Protections may review study records during required reviews.
You should be aware that the experiment is not being run from a 'secure' https server of the kind typically used to handle credit card transactions, so there is a small possibility that responses could be viewed by unauthorized third parties such as computer hackers. In general, the web page software will log as header lines the IP address of the machine you use to access this page, e.g.,102.403.506.807, but otherwise, no other information will be stored unless you explicitly enter it.

Costs to You:
There are no costs to you besides your time for being in this study.

Questions about the Study:
If you have any questions about the study, you may contact Dr. Walker or Dr. Catrambone by telephone at (404) 894-2680 or via email at: bruce.walker@psych.gatech.edu richard.catrambone@psych.gatech.edu

Questions about Your Rights as a Research Participant:

- Your participation in this study is voluntary. You do not have to be in this study if you don't want to be.
- You have the right to change your mind and leave the study at any time without giving any reason or penalty.
- Any new information that may make you change your mind about being in this study will be given to you.
- You do not waive any of your legal rights by signing this consent form.

If you have any questions about your rights as a research participant, you may contact the Georgia Institute of Technology Office of Research Integrity Assurance at IRB@gatech.edu.

By selecting “agree” below, you are providing you are indicating that you have read this consent form and consent to participate in this research study.

Appendix E

MOS Excel Test Item Performance: Point Bi-serial Correlations

Question	Pearson's *r*	*p*
Q1.1	0.261	0.354
Q1.2	0.059	< .001
Q1.3	0.427	< .001
Q1.4	0.287	< .001
Q1.5	0.377	< .001
Q2.1	0.345	< .001
Q2.2	0.357	< .001
Q2.3	0.364	0.004
Q2.4	0.181	< .001
Q2.5	0.235	< .001
Q3.1	0.246	< .001
Q3.2	0.384	< .001
Q3.3	0.432	< .001
Q3.4	0.270	0.370
Q3.5	0.058	< .001
Q4.1	0.286	< .001
Q4.2	0.239	< .001
Q4.3	0.375	< .001
Q4.4	0.336	< .001
Q4.5	0.327	0.005
Q4.6	0.180	< .001
Q4.7	0.271	0.191
Q4.8	0.084	< .001
Q4.9	0.392	< .001
Q4.10	0.564	< .001
Q5.1	0.402	0.001
Q5.2	0.204	< .001
Q5.3	0.266	< .001
Q5.4	0.436	< .001
Q5.5	0.446	<.001

Appendix F

Thematic Analysis Codebook

CAN_DO theme	Definition
simple formulas	specifically mention SUM, COUNT, AVG, PRODUCT etc or Basic/simple/easy formulas or calculations
create graphs/charts	mention any simple graphs or charts. mention combination of tables, charts, and graphs
input data	talk about data entry and typing out information in cells. Other items included = lists & entering data/time
sort/filter	Mention sorting or filtering the data in any way. Specifically use either term or mention alphabetizing
create table	create a simple, basic table. Mention of a table or organizing data into a table. NO mention of graphs/charts
formatting	Talk about formatting (not conditional formatting). Mention of adding color or style to a cell or table
formulas	general mention of formulas. No mention of a specific function or if it is basic or advanced. Just general formula knowledge.
shortcut keys	mention cut, copy paste, tab, autofill, shortcut keys, drag and drop
manage spreadsheet/ workbook	create, rename, protect and/or move new spreadsheets/workbooks/documents
organize data	specifically state "organize" data. Vague and unsure of what category this could fit into
manipulate cells	add, delete, move, hide, resize, select, or make cell absolute
track financial info	use excel for budgeting or finance tracking
conditional formatting	specifically mention conditional formatting or define conditional formatting (formatting based on certain criteria)
N/A	write in random words unrelated to the questions such as idk, I know nothing, not sure, make a rainbow, do a somersault
utilize functions/commands	mention functions or commands. Mention specific functions such as text to columns,
manipulate columns/rows	add, delete, move, freeze rows/columns
create report/presentation	create a visualization (not a chart) or writing up a report via excel
pivot table	mention pivot tables or pivot charts. Pivot charts was much more rare.
keep records	general data tracking, scheduling, inventory
create database	store/collect large amounts of data. Large is the key word
data analysis	specifically mention analyzing the data (no mention of formulas, just actual analysis)
insert object	just inserting objects.
templates	mention creating templates. This may fit into manage spreadsheet/worksheet
troubleshoot	troubleshoot/fix errors as they come up
manage data	import/export data
macros/VBA	mention macros of Visual Basic coding or coding in general within excel

CANNOT DO Theme	Definition
pivot table	mention of creating or editing pivot tables/charts
advanced formulas	mention writing their own complex/advanced formulas, algorithms, or computations

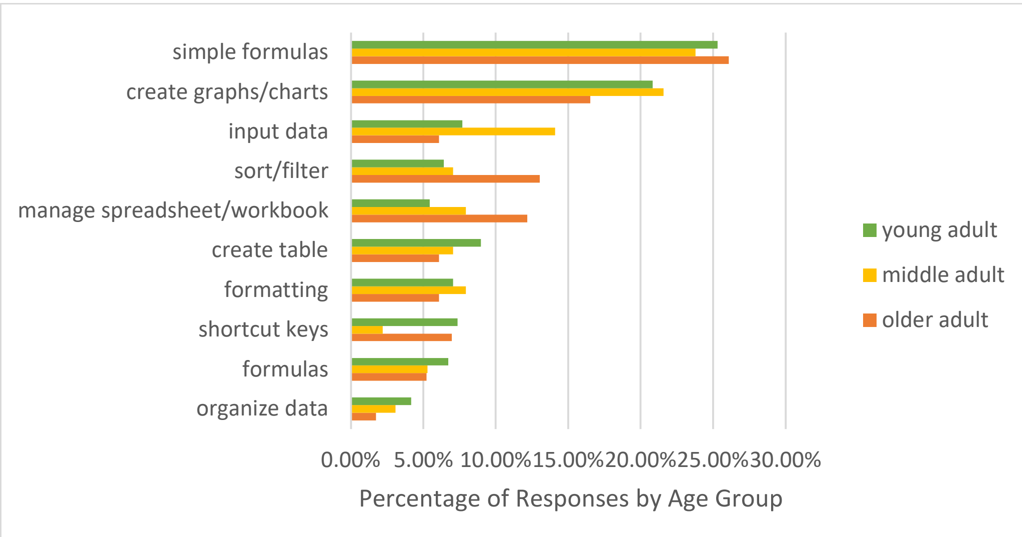
N/A	write in random words unrelated to the questions such as idk, I know nothing, not sure, make a rainbow, do a somersault
macros/VBA	mention macros of Visual Basic coding or coding in general within excel
data analysis	specifically mention analyzing the data (no mention of formulas). General mention of analysis not specific types or specific difficulties.
create graphs/charts	mention any simple graphs or charts. mention combination of tables, charts, and graphs
formulas	general mention of formulas. No mention of a specific function or if it is basic or advanced. Just general formula knowledge.
create complex visuals	create visuals that are more than just regular graphs/charts
conditional formatting	specifically mention conditional formatting or define conditional formatting (formatting based on certain criteria)
formatting	Talk about formatting (not conditional formatting). Mention of adding color or style to a cell or table
sort/filter	Mention sorting or filtering the data in any way. Specifically use either term or mention alphabetizing
utilize functions/commands	mention functions or commands. Mention specific functions such as text to columns,
vlookup	specifically mention vlookup or define vlookup
manage data	clean, import, export, consolidating data
simple formulas	specifically mention SUM, COUNT, AVG, PRODUCT etc or Basic/simple/easy formulas or calculations
manage spreadsheet/worksheet	create, rename, protect and/or move new spreadsheets/workbooks/documents
Forecast	mention of Forecast and Forecast tools like Goal Seek
troubleshoot	troubleshoot/fix errors as they come up
track financial info	use excel for budgeting or finance tracking
automation	auto updating/automation
shortcut keys	mention cut, copy paste, tab, autofill, shortcut keys, drag and drop
work with multiple sheets	mention working across multiple tabs/sheets
add-ins	add-ins
input data	talk about data entry and typing out information in cells. Other items included = lists & entering data/time
keep records	general data tracking, scheduling, inventory
queries & connections	Queries and Connections tools. Creating and editing queries and connections
create table	create a simple, basic table. Mention of a table or organizing data into a table. NO mention of graphs/charts
manipulate columns/rows	add, delete, move, freeze rows/columns
complex table	create a simple, basic table. Mention of a table or organizing data into a table. NO mention of graphs/charts
create database	store/collect large amounts of data. Large is the key word. Mention database
manipulate cells	add, delete, move, hide, resize, select, or make cell absolute
organize data	specifically state "organize" data. Vague and unsure of what category this could fit into
create calendar	state create calendar
create templates	mention creating templates. This may fit into manage spreadsheet/worksheet
create form	state create form
price	mention of cost of excel or keeping up with excel subscription

problem solving	use excel for problem solving
customize excel	mentioned "customizing" excel
advanced formatting	specifically state advanced formatting
data tools	mention general of data tools, data validation, text to columns, remove duplicates

Appendix G

Figure 1.

Top 10: Perception of Average Excel User Capabilities by Age Group



Note. Each of the 250 participants provided 3 responses for a total of 750 responses to the question: What do you think the average excel user can do? Percentages for each age group were calculated by taking the total number of responses for each category and dividing by number of total participants in that specific age group. This allowed for comparison between the uneven distribution of ages. Young adults (<30), Middle Adults (30 – 49), Older Adults (50+)

Figure 2.

Top 10: Perception of Average Excel User Capabilities by Gender

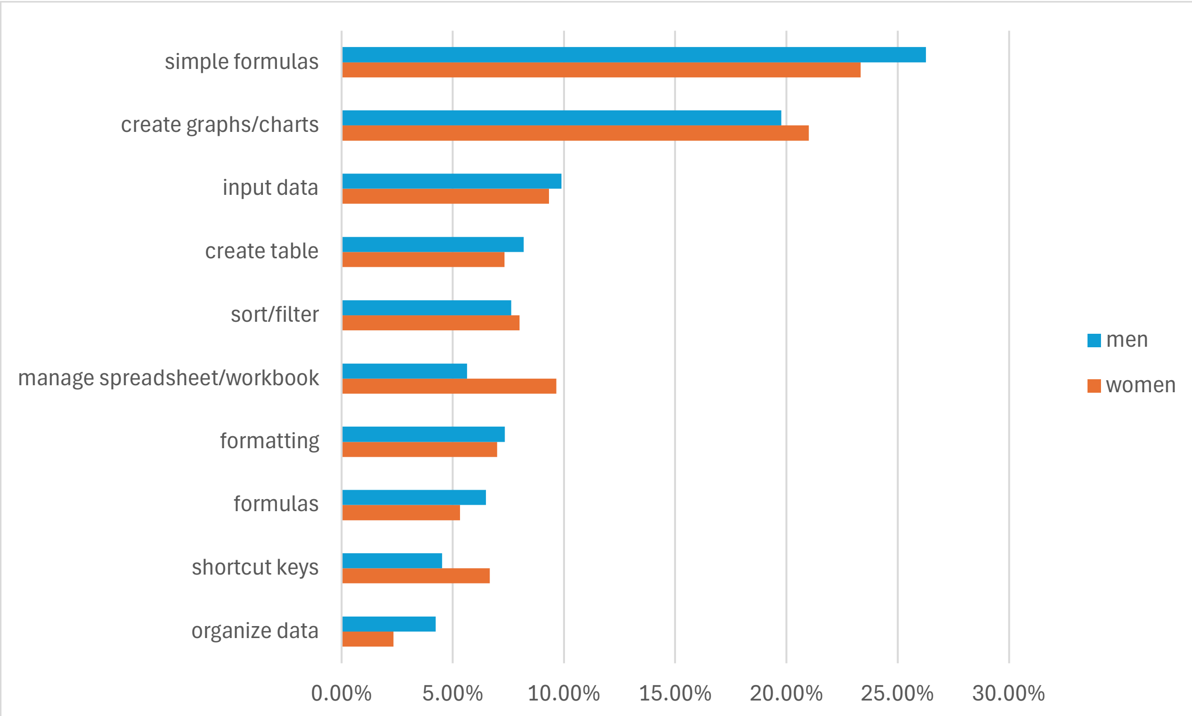


Figure 3.

Top 10: Perception of What is Outside Average Excel User Capabilities by Age Group

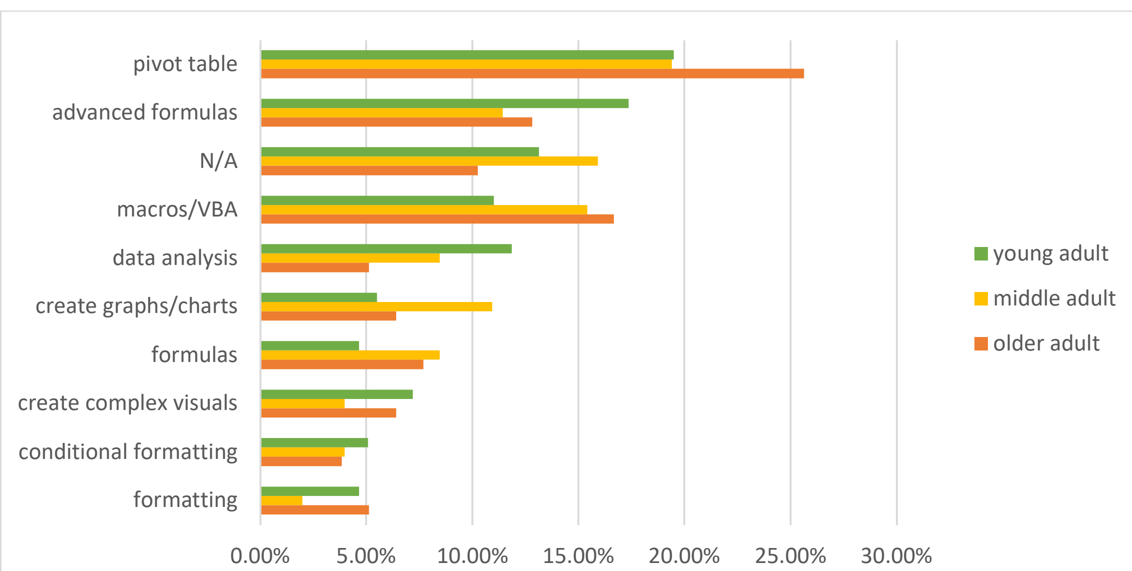


Figure 4.

Top 10: Perception of What is Outside Average Excel User Capabilities by Age Group